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GUEST EDITORIAL

Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations

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Introduction

Much attention is currently being paid in both the academic and practitioner literatures to the value that organisations could create through the use of big data and business analytics (Gillon *et al*, 2012; Mithas *et al*, 2013). For instance, Chen *et al* (2012, p. 1166–1168) suggest that business analytics and related technologies can help organisations to 'better understand its business and markets' and 'leverage opportunities presented by abundant data and domain-specific analytics'. Similarly, LaValle *et al* (2011, p. 22) report that top-performing organisations 'make decisions based on rigorous analysis at more than double the rate of lower performing organisations' and that in such organisations analytic insight is being used to 'guide both future strategies and day-to-day operations'.

We argue here that while there is some evidence that investments in business analytics can create value, the thesis that 'business analytics leads to value' needs deeper analysis. In particular, we argue here that the roles of organisational decision-making processes, including resource allocation processes and resource orchestration processes (Helfat *et al,* 2007; Teece, 2009), need to be better understood in order to understand how organisations can create value from the use of business analytics. Specifically, we propose that the first-order effects of business analytics are likely to be on decision-making processes and that improvements in organisational performance are likely to be an outcome of superior decision-making processes enabled by business analytics.

This paper is set out as follows. Below, we identify prior research traditions in the Information Systems (IS) literature that discuss the potential of data and analytics to create value. This is to put into perspective the current excitement around 'analytics' and 'big data', and to position those topics within prior research traditions. We then draw on a number of existing literatures to develop a research agenda to understand the relationship between business analytics, decision-making processes and organisational performance. Finally, we discuss how the three papers in this Special Issue advance the research agenda.

Prior research traditions on big data and analytics

Recent years have seen a significant interest in the potential of 'big data' and 'analytics' to transform the competitive landscape and to improve organisational performance. For instance, Davenport & Harris (2007) and Davenport *et al* (2010) describe many examples of successful use of data and analytics and offer a number of managerial strategies for successfully exploiting their potential. Similarly, Wixom *et al* (2013) describe the successful use of data and analytics by a fashion retailer (Wixom *et al,* 2013), and Anderson-Lehman *et al* (2004) describe a similar experience at an airline company.

'Big data' and 'analytics' are recent buzz words in both the management and IS literatures. However, the ideas presented under these labels have a longer history. A number of scholars presented similar ideas when data warehousing and data-mining technologies were beginning to mature. For instance, Watson *et al* (2002) (Wixom and Watson, 2001; Goodhue *et al,* 2002; Anderson-Lehman *et al,* 2004) discussed the strategic and operational benefits of integrating organisational data from multiple internal and external data sources into a data warehouse, as well as the factors affecting the success of data warehouses. Going further back to the mid-1990s, Fayyad *et al* (1996) described a process of extracting useful knowledge from large volumes of data using data-mining techniques; Sasisekharan *et al* (1996) described an application of data-mining techniques to improve the performance of telecommunication networks; and Simoudis (1996) discussed the theory, applications and limits of data mining.

The notion that data and analytical tools can be used to diagnose and improve performance pre-dates even the discussions of data warehousing and data mining in the literature. For instance, Zuboff (1985, 1988) coined the term informate to describe that specific capability of IT. Zuboff (1985, p. 8) argued that while IT automates processes, it 'simultaneously generates information about the underlying processes through which an organisation accomplishes its work'. Further, Zuboff argued that this new information can be used to 'create a different and potentially more penetrating, comprehensive, and insightful grasp of the business. This, in turn, can serve as the catalyst for significant improvement and innovation in the production and delivery of goods and services, thus strengthening the competitive position of the firm'. Drawing on Zuboff's work, Kohli and Kettinger (2004) describe how a hospital was able to improve performance drawing on the informating capabilities of IT. In the same vein, Sharma *et al* (2010) argue that the use of Total Quality Management techniques by Japanese automakers is also an instance of the use of business analytics by industry.

An even earlier tradition in IS research that discusses the use of data and analytical models to improve performance is the research on Decision Support Systems and Executive Support Systems (Huber, 1990; Leidner and Elam, 1995). An excellent history of this tradition, dating back to the 1960s is provided by Dan Power on the DSS Resources webpage (http://dssresources.com/). A recent compendium (Burstein and Holsapple, 2008) also offers a detailed overview of that tradition.

Within the history of modern management scholarship, Simon's (1947, 1956) seminal works laid the theoretical foundations for examining the impact of decision-support technologies on managerial decision making, on organisational decision-making processes, and on the relationship between decision-making processes and organisational performance. Simon's notion of structured *vs* unstructured decisions has been extensively researched in the context of managerial decision making. Similarly, Simon's intelligence-design-choice model has been extensively used to understand the very same questions that have once again become pertinent in the current wave of technological advancement in decision-support technologies, viz., business analytics.

Finally, to put the issue of data and analytics into an even longer historical perspective, the ancient practice of conducting censuses by States, which is current even today, is also underpinned by the beliefs that data is valuable and that analysis of data can provide insights that can be used to inform decisions and policy initiatives.

Towards a research agenda

Despite a long tradition of research in this area, we argue here that more attention needs to be paid to the roles of behavioural, organisational and strategic issues in understanding the impact of business analytics on organisations and organisational performance. In particular, not much attention has been paid to how decision making and resource allocation processes might need to change in order to capture value from the use of business analytics. The focus has largely been on how managers can make better decisions once they have better data and analytic tools for decision making. The focus on discrete decisions and the improvements in discrete decisions that business analytics can enable has obscured the potentially much larger impact that business analytics can enable in conjunction with changes in organisational decision-making processes (Sharma *et al,* 2010; Sharma & Shanks, 2011).

An implicit assumption underpinning the recent business analytics literature has been that organisations can capture value while continuing to function as before. The assumption that advances in technological capabilities are sufficient by themselves for organisations to capture value is not new. Such assumptions underpinned the initial introduction of Enterprise Systems, viz., that organisations could capture performance gains from Enterprise Systems without undergoing major structural and process changes. Later research identified the critical roles of process and structural changes in capturing the potential benefits from the use of Enterprise Systems (Markus & Tanis, 2000; Markus, 2004). Similar assumptions could be seen during the introduction of Knowledge Management Systems into organisations (Kankanhalli *et al,* 2005), where it became apparent from subsequent research that accompanying changes in processes and structure were necessary to obtain benefits from such systems (Kankanhalli *et al,* 2011).

Drawing on such earlier research, we argue here that organisational decision making and resource allocation processes will need to transform if organisations are to obtain performance gains from their investments in business analytics. Below we propose three research questions that advance the above research agenda:

- How does the use of business analytics influence organisational decision-making processes?
- How is the use of business analytics influenced by organisational decision-making processes?

- What are the joint effects of the use of business analytics and organisational decision-making processes on organisational performance?

In the following sections, we elaborate on the above research agenda within three stages of using business analytics to obtain performance gains: the data to insight stage, the insight to the decision stage and the decision to the value stage.

Data to insight

Current technologies make available to analysts and managers a vast amount of structured and unstructured data from a variety of sources (Sharma *et al,* 2010). Further, analysts and managers today have available to them a powerful set of data analysis, data mining and data visualisation tools (Davenport and Harris, 2007; Davenport *et al,* 2010). However, despite the hopes of many, insights do not emerge automatically out of mechanically applying analytical tools to data. Rather, insights emerge out of an active process of engagement between analysts and business managers using the data and analytic tools to uncover new knowledge. More importantly, those engagements take place within existing structures and processes for decision making. A better understanding of the insight generation process is important for understanding how the use of business analytics leads to improved performance.

Anecdotal evidence in the scholarly and practitioner literatures describes a number of instances of the use of business analytics to generate insights that are converted to value through subsequent competitive actions (Sharma and Shanks, 2011). For instance, Kohli (2007) describes a number of insights that managers at United Parcel Service (UPS) gained through analysis of data in their highly integrated data warehouse. Those include cost and profitability estimates of individual delivery routes, plausible explanations for a growing backlog of packages and estimates of the amount of fuel that could be saved by minimising the number of left turns on their delivery routes. Similarly, Anderson-Lehman *et al* (2004) describe insights into pricing, scheduling and customer loyalty that Continental Airlines gained through use of its data warehouse; and Watson (2001) describes a number of insights that Harrah's gained into the gambling behaviour of its casino customers.

The process of generating insights from data generally involves multiple actors from different parts of the organisation. The composition and structure of those teams is often an outcome of managerial decisions that are taken within existing decision-making routines. Importantly, those routines can both enable and constrain the ability of those teams to generate insights. The effects of team composition and existing structures on decisions and decision making are subtle but powerful. For instance, Henderson & Clark (1990) describe a case where R&D teams could not see the strategic significance of emerging technologies for their products even though they had access to relevant information. Henderson and Clark attribute this failure to the composition of the teams, which reflected existing product and organisational architectures. The teams, though cross-functional in their compositions could not transcend the existing cognitive frameworks of individual team members, which were shaped by existing organisational boundaries. Team members could see the significance of the emerging technologies for the specific components of the product architecture they were responsible for. However, they could not see the significance of the emerging technologies for the overall architecture of the product. The teams were collectively unable to grasp the strategic insights that could have been gleaned from the information that was available to them. Similarly, Howells (2005) describes a pattern in the VLSI industry where incumbents in one generation of the technology were repeatedly overtaken by new entrants in the next generation. This happened despite significant investment and expertise developed by the incumbents in the emerging technologies.

The above discussion suggests that there is a need to gain a better understanding of how existing organisational structures, routines and decision-making processes affect the ability of analysts and managers to generate insights from the use of business analytics. This is an important area of research as improving the effectiveness of the insight generation process can dramatically improve the value of business analytics for organisations. Specifically, we suggest that researchers focus on the following question:

- How do existing organisational structures, routines and decision-making processes influence the ability of managers and analysts to generate insights from data?

The above examples illustrate the complex relationships between data, analytical tools and human sense making. Lycett (2013) argues that business analytics enables analysts and managers to engage in an IT-driven sense-making process in which they use the data and analysis as a means to understand the phenomena that the data represent. Lycett refers to this process as 'datafication'. Lycett further argues that despite the data-driven nature of analytics-based sense making, pre-existing frames of reference carried by analysts and managers have an important influence on what data elements are selected to describe the phenomena and what patterns and relationships connecting the data elements are inferred from the data. Those insights are then used by managers and analysts to weave a narrative making sense of the world and then to construct action repertoires that make those interpretations explicit. Importantly, those frames of reference are embedded in the cognitions of analysts and managers and operate in a sub-conscious manner.

Lycett (2013) argues that even though business analytics tools make it easy to spot statistical patterns, trends and relationships, the critical next step of understanding the causes behind those patterns is still important in order to undertake actions that generate value. Arguably, machine learning algorithms can detect patterns and even improve their own performance over time. Such machine learning algorithms are already being used to take decisions and actions, as in Netflix's recommender system described by Lycett. Other examples of such deployment of machine learning have also been described in the literature, such as in detecting credit card fraud and automated trading of stocks. However, human insights are still involved in 'accepting' the insights generated via machine learning as being valid and useful, in 'deciding' to deploy them to run operations in an unguided manner, and in 'accepting' the refinements to the algorithms generated via machine learning as being valid. Lycett's analysis suggests an important question for future research:

- How can human sense making and machine learning work together to improve the generation of insights from the use of business analytics?

A parallel stream of research has focused on how to make the insight generation process more effective. For instance, Davenport (2006), Davenport and Harris (2007) and Davenport *et al* (2010) suggest the business analytics competency centre as a structural device that might make the business analytics-enabled insight generation process more effective. They conceive of the competency centre as a centralised unit housing expertise in business analytics and providing a service to business units. The competency centre is presented as a solution to overcome the shortage of trained analytical personnel. Anecdotal evidence, as well as our own research (Shanks *et al,* 2010, 2011; Shanks and Sharma, 2011) suggests that such central units do not connect very well to business units and that they find it difficult to convert their insights into value through competitive actions by business units. More importantly, it is not clear how such a structural innovation can address the limitations to insight generation discussed here. Nevertheless, Davenport *et al's* (2010) discussion draws attention to the need for further research on an important research question:

- How do the structures and processes of decision making influence the ability of insight generation teams to generate insights from the use of business analytics?

Insight to decision

Just as it is critical to generate meaningful insights, it is as vital to transform insights into decisions that can create value. Insights, which refer to deep and intuitive understanding of phenomena, need to be leveraged by analysts and managers into strategic and operational decisions to generate value (Sharma *et al,* 2010; Lycett, 2013). Here, we refer to decisions as the end of deliberation and the commitment of specific and complementary resources to a chosen course of action (Davis and Devinney, 1997). There is almost an axiomatic belief within much of the business analytics literature that good insights lead to better decisions, and that 'big data' leads to 'big impact' (Chen *et al,* 2012). For instance, Gangadharan and Swami (2004) suggest that the use of business intelligence allows for a better understanding of business problems and opportunities through analysing current operations that can lead firms to uncover new revenue sources or elicit cost savings.

While it is reasonable to expect that there is a relationship between the use of business analytics, and better insights and decisions, it is not clear under what conditions those better outcomes would be observed. There are two broad issues involved here that need to be explored in future research.

First, there is no one-to-one correspondence between an insight and a specific course of action to exploit that insight. Simon's classic work models decision making as a three-step process of intelligence, design, and choice, and where multiple alternatives emerge in the design phase following the intelligence phase of decision making (Simon, 1947). Insights, including those based on an understanding of trends, operations, customers and suppliers are likely to suggest multiple options for exploiting them and converting them to value. Some options may be obvious whereas others may be an outcome of a more creative process, for instance, involving analysts relaxing current constraints and imagining new business models. Sharma *et al*'s (2010) analysis of Kohli's (2007) case study illustrates the complexity involved in converting insights into options and decisions. Sharma *et al*'s (2010) argue that while the use of business analytics may have generated the insight that rural routes were losing money, UPS' decision to outsource those routes to a competitor was not an obvious one. It is common in such situations for multiple options to be suggested at this stage and it is likely that UPS managers would have discussed multiple options at this stage. Further, the decision that they finally took would most likely have required approval at a fairly high level, underscoring the role of organisational decision-making processes in converting insights to decisions.

The second issue that needs further research is that organisational decision-making processes have an important bearing on how insights are converted into decisions. Prior literature provides many illustrations of situations where good ideas, insights and even breakthrough products have been rejected by organisations, only to become blockbuster successes for other organisations. Stories of Xerox's decision not to pursue the development of the personal computer; IBM's late push into the personal computer and its decision to protect the intellectual property on the BIOS while outsourcing the development and intellectual property of the operating system; Microsoft's late push into the internet space; and Kodak's catch-up in the development of the digital camera are the stuff of legends and, perhaps many urban myths. Nevertheless, they do underscore the point that organisational decision-making processes have an important bearing on the efficacy of converting insights into decisions.

We argue here that while insights serve as an important input to decision-making processes, specific decisions taken are influenced by a host of other factors. Complex organisational decision-making processes are often involved in creating options, evaluating them and committing to a particular option. Notwithstanding the issues involved in deciding what a 'good' decision is (Drucker, 1967; Vroom and Yetton, 1973), good insights need not necessarily result in good decisions and bad decision are possible outcomes too. This highlights an important question for future research:

- How do organisational decision-making processes influence the conversion of business analytics-based insights into good decisions?

The roles of contextual and psychological factors on the quality of decision making have been extensively investigated in prior research traditions. In particular, Simon's (1947, 1956) early works on decision-making processes and subsequent research into the behavioural theory of the firm (March, 1994), the psychology of decision making, and the effects of heuristics and biases on decisions (Hogarth, 1987) have significantly advanced our understanding of those issues. A key finding from those traditions of research is that organisational decision-making processes are often characterised by satisficing behaviours, which are likely to result in decisions that may be suboptimal (Simon, 1956). In particular, complex circumstances, limited time and inadequate mental computational power have been found to impact the quality of decisions (Bok *et al,* 2012). For instance, Rowe (2005) finds that the use of analytics-based risk assessment in a bank influenced the decision processes of financial advisors. Importantly, he also found that the bank's practice of using different risk governance processes for different customer segments influenced the extent to which the advisors' decisions were influenced by analytics-based risk assessments for specific customer segments; as did the extent to which the advisors had personal knowledge of the clients whose risks were being assessed. Extending that literature, Gavetti (2005) describes how existing organisational structures influence the cognitions and decisions of business unit managers. Specifically, he argues that the cognitions of business unit managers are likely to be more constrained in contexts where corporate management exerts strong control over the strategies of business units and where business units share economies of scale and scope with other business units. Contributing to that literature, Blyler and Coff (2003) argue that social capital is an important resource that enables the pooling of knowledge and resources across organisational boundaries, and an important antecedent of decision quality as well as decision implementability.

We argue here that further research is needed to identify the process and conditions under which insights lead to better quality decisions. The above stream of research raises a number of important questions for future research:

- Can organisations use business analytics to compensate for the limitations of managerial and organisational decision-making processes that have their roots in satisficing behaviour, cognitive limitations and structures of social capital and, if so, how?

Decision to value

While much discussion has focused on the ability of business analytics to generate better insights and decisions, the focus on the potential of business analytics to capture value has been limited. The implicit assumption underpinning that discourse appears to be that if the quality of decisions can be improved through the use of business analytics, then the question of how organisations can create value from those decisions is a trivial one. Extending that discourse, we highlight here two uncertainties associated with converting decisions to value – the uncertainty of successfully implementing decisions and the uncertainty associated with the success of strategic actions. We also discuss the potential role of business analytics and resource allocation processes in mitigating those uncertainties.

While high-quality decisions may be a good starting point, it is by no means certain that those decisions will be successfully implemented. Indeed, prior research argues for at least two criteria characterising 'good' decisions. One criteria refers to the 'quality' of the decision, that is, whether the decision is capable of achieving its objectives; the other refers to the 'acceptance' of the decision, that is, its acceptance by subordinates and other stakeholders responsible for the successful implementation of the decision (Drucker, 1967; Vroom and Yetton, 1973; Sutanto *et al,* 2008–2009). Research into the acceptability of decisions suggests that decision-making processes have an important bearing on the acceptability of decisions. Specifically, Vroom and Yetton (1973) suggest that the level of influence and participation that subordinates and key stakeholders have on a decision has an important bearing on its acceptance and, presumably, its successful implementation.

Arguably, the use of business analytics can help to improve the quality of decisions. However, it is not clear if business analytics can be used to improve the acceptance of decisions in any way. Our anecdotal research suggests that insight-generation and decision-making processes associated with the use of business analytics often do not involve key stakeholders from functional areas who will be responsible for implementing those decisions (Shanks *et al,* 2010; Shanks and Sharma, 2011). Although cross-functional teams are often employed to work with business analytics, key stakeholders who 'own' the resources required to implement decisions are often not a part of those teams. If what we have observed is a systematic pattern, it would likely show up in cross-sectional research as a negative correlation between the use of business analytics in decision making and the successful implementation of those decisions.

The above discussion raises important questions for future research. These questions have important implications for the abilities of firms to capture value from the use of business analytics:

- How do decision-making processes influence the successful implementation of decisions arising out of the use of business analytics?
- How can business analytics be used to improve the acceptance of decisions?

Further, recent research into the dynamic capabilities framework suggests that an organisation's search and select capability and its asset orchestration capability have an important bearing on its performance (Helfat *et al,* 2007; Teece, 2009). While it is clear that business analytics can improve an organisation's search and select capability, it is not clear how it might affect its asset orchestration capability. Organisational assets and resources are typically governed under formal or informal structures and managers will typically need to negotiate across organisational boundaries to access assets they need to implement their strategies. There will necessarily be heterogeneity in those capabilities within and between organisations and also between decisions and contexts. Managers face uncertainty regarding the availability of resources to implement strategies, testifying to the important role of asset orchestration capability in implementing strategic actions. Although research into the factors affecting asset orchestration capabilities is still emerging, an important question for future research is:

- How can business analytics be used to improve an organisation's asset orchestration capability?

The key role of asset orchestration capabilities suggests that governance structures might need to evolve as organisations move towards a greater reliance on the use of business analytics to support strategic decision making. In general, the implementation of strategies is a business unit or a functional responsibility. However, business analytics-supported strategies are likely to place increasing reliance on the use of IT assets and resources even during the implementation stages. The roles of the CIO, the IT function and the heads of business and functional units will need to evolve to accommodate the blurring of institutionalised roles and structures. Organisations may need to focus more on information governance rather than the conventional focus on the governance of IT artifacts (Tallon *et al,* 2013). Important questions for future research include:

- How do governance structures evolve as a result of increasing penetration of business analytics?
- What governance structures are more effective in capturing value from business analytics-supported strategic decision making?

A second source of uncertainty in converting decisions to value arises from outcome uncertainty. This refers to the uncertainty surrounding the outcomes as a result of organisational actions. Organisations generally undertake strategic actions in the hope of successful outcomes. However, actual outcomes often depart significantly from expectations and uncertainty of outcomes is often factored into the decision-making process (Clemen, 1991). Much of this uncertainty is outside the control of the actors and the organisation. It is not clear if decisions supported by business analytics would be affected in any different manner by outcome uncertainty. Notwithstanding the effects of the use of business analytics on the quality and acceptance of decisions, which could have an independent effect of reducing outcome uncertainty, an important question for future research is:

- How can business analytics be used to reduce the outcome uncertainty associated with strategic decisions?

Summarising the above discussion, we have argued that the path from the use of business analytics to organisational performance is complex. In particular, the mediating roles of decisions and competitive actions, as well as the moderating roles of organisational decision-making processes, resource allocation processes, governance processes, search and select capabilities, and asset orchestration capabilities need to be investigated in further research. Key aspects of our arguments are summarised in Figure 1.

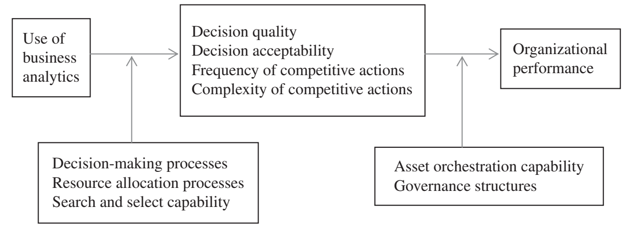

Figure 1 A research model to understand the joint effects of business analytics use and organisational decision-making processes on organisational performance.

Directions for practice

The above discussion also has important implications for managers engaged in using business analytics to improve performance. The potential value that could be created and captured through the use of business analytics is one of the key motivations for why organisations are making substantial investments in those technologies. Similar motivations have underpinned prior investments in technologies such as Executive Information Systems, Customer Relationship Management Systems and Business Intelligence Systems that can be considered as precursors of business analytics. Researchers investigating the value and returns captured by organisations from those earlier investments have identified a number of benefits arising from the use of those technologies. These include tangible benefits such as improved information flows, and intangible benefits such as improved customer knowledge, one-to-one marketing effectiveness, customer satisfaction and consumer surplus (Mithas *et al,* 2005; Mithas *et al,* 2006).

However, the pathways from investments in those technologies to economic value are not obvious. In particular, researchers have identified that the effects of investments on indicators of value creation such as stock returns and stock risk are not direct; rather, those effects are mediated by their effects on variables such as customer satisfaction (Fornell *et al,* 2006, 2009). Researchers have also documented the value of being a data-driven organisation and shown that organisations with better information management capabilities achieve improved performance in many different ways (Mithas *et al,* 2011; Mithas *et al,* 2012; Saldanha *et al,* 2013; Schryen, 2013). Mithas *et al* (2013) and Gillon *et al* (2014) identify six pathways to value through the use of analytics-based capabilities, namely, Adding volume and growth, Differentiating, Reducing costs, Optimising risks, Improving industry structure (also innovating with products and services), and Transforming business models and business processes for continued relevance in a changing landscape (captured in the acronym ADROIT).

Taken together, the above findings suggest that the manner in which organisations deploy technologies has an important bearing on their ability to create and capture value. In particular, managers need to pay particular attention to transforming their decision-making processes if they are to capture the value that is possible through the use of business analytics. Business analytics is best thought of as a real options generator (Sambamurthy *et al,* 2003; Fichman *et al,* 2005). Unless those real options are exercised through further investments of managerial and financial resources, they do not generate any value for organisations (McGrath and MacMillan, 2000). It is important that organisations transform their decision making and resource allocation processes to accommodate the evaluation and resourcing of real options generated by the use of business analytics.

Commentaries on papers in the Special Issue

The three papers in this Special Issue advance the above research agenda in their own ways.

Frisk *et al* (2013) open up the discussion of decision-making processes and argue that the literature has not paid adequate attention to how alternatives are generated for evaluation. They argue that decision makers are often constrained by institutionalised norms that constrain the search for alternatives. Consistent with the research model developed here (Figure 1), such institutionalised decision-making processes can have a negative impact on the quality and acceptance of decisions, as well as on the organisation's ability to undertake strategic actions.

This indeed was the case in the Swedish Fire and Rescue Service, the site where Frisk *et al* (2013) carried out their field work. The FRS had an existing decision-making process of evaluating IT investments in a particular manner that constrained the information that was sought for making decisions as well as the people and roles from whom information was to be sought. As a result, alternatives that could be considered were not even identified. As part of their action research, the authors opened up the decision-making process to enable many more people and roles to contribute information to the decision-making process. The interaction between multiple roles and participants surfaced many insights that shaped the subsequent decision-making process as well as the quality and acceptance of decisions.

Arguing from a design perspective, Frisk *et al* (2013) propose that decision making is less about choosing between alternatives and more about a creative process through which alternatives are discovered. The design approach to decision making relies on insights based on analysis of data from multiple sources and the discovery of creative options through immersion in data. The use of business analytics can help organisations move towards decision-making processes that are more informed by insight-based design and creativity. A key takeaway from this paper is that while much attention has been paid to the intelligence and choice stages of the decision-making process, the design stage is equally important and needs to receive more attention from both managers and researchers.

Huang *et al* (2014) illustrate the role of joint effects of business analytics use and asset orchestration capability on organisational performance (Figure 1). They contribute towards enriching our understanding of how firms can develop operational agility to sense changes in their turbulent business environment and conceive competitive actions.

On the basis of an in-depth case study of Haier, one of the largest household appliance manufacturers in China, Huang *et al* (2014) argue that operational agility is a key capability that influences success in rapidly changing business environments. Yet, they find that the literature is lacking in answering how operational agility can be developed by firms. Their study reveals information-processing capability, a capability that could be enhanced through business analytics, as a key antecedent of operational agility. Their model suggests that operational agility is achieved through a two-step process of construction of IT-enabled information-processing network and the implementation of governance structures exercising organisational control. Thus their study proposes that the use of business analytics in conjunction with changes in structure and process enables the development of information-processing capability and operational agility. Huang *et al* (2014) contribute to the research agenda described above (Figure 1) by throwing light on the mechanisms for and the conditions under which business analytics help to develop key capabilities that contribute to organisational performance.

Habjan *et al* (2014) illustrate the effects of use of business analytics on the quality and acceptance of decisions, as highlighted in Figure 1.

Habjan *et al* (2014) conducted an exploratory comparative case study of three medium-sized Slovenian transport firms that implemented the same Geographical Positioning System (GPS) over the same period of time. Their findings suggest that increased use of information generated by GPS improved the quality of operational decision making, which then contributed to improved organisational performance. Their research also suggests that organisational factors (such as top management support, project management of GPS implementation, financial support, end user involvement, rewarding, training and employee resistance) and a firm's information management capability (in terms of availability of quality information in decision making, software tools for connectivity and access to information, IT systems integration post-GPS adoption and adaptability of the infrastructure to emerging business needs) can moderate the effect of use of GPS-enabled information in operational decision making on organisational performance. This study illustrates many of the issues highlighted in the research agenda described above (Figure 1) as firms navigate the data → insight → decision → value cycle to convert the use of business analytics into value.

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