The impact of data analytics on decision making processes and firm performance

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Abstract

This paper investigates decision making in data-intensive organisations and its impact on organisational structure and firm performance. It is increasingly evident that data analytics are playing a crucial role in supporting organisations' managerial and strategic decision making. This study shows that elements such as empowerment and organisational structure, play an important mediating role in enabling decision making. This study looks into three case studies, and the results show that these cases have distinctively different approaches to data analytics, and that their decision making processes are directly affected by how they are structured and the level of empowerment of the decision makers.

Keywords

Decision making, organisational structure, information processing, firm performance.

Introduction

According to Bromiley (2004), among the primary objectives of strategic management research is to provide recommendations for improving firm performance. Although studies focusing on firm performance in strategic management research abound, the theme of decision making frequently emerged among the most important factors influencing performance (Brouthers et al., 1998; Baum and Wally, 2003; Kunc and Morecroft, 2010; Csaszar, 2012). The focus of such research varied, where some studies were more concerned with the decision making process and its effectiveness (Fredrickson, 1986; Elbanna and Child, 2007) whereas others were, for instance, more interested in the impact of decisions on firm performance (Baum and Wally, 2003; Kunc and Morecroft, 2010). Particularly, studies looking into the speed of decision making attempted to research the impact of fast decisions on firm performance (Eisenhardt, 1989b; Judge and Miller, 1991; Oliver and Roos, 2005; Baum and Wally, 2003). Most of these studies focused on high velocity environments, which present managers with the challenges of having to make decisions based on ambiguous information and in environments characterised by constant change (Oliver and Roos, 2005). In such contexts, it has even been suggested that attempting to over search for information prior to making decisions leads to potentially loosing valuable opportunities (Klein, 1998).

It is a fact that nowadays organisations are increasingly dealing with massive amounts of data for which they are ill equipped due to the variety and the increasingly unstructured nature of these data (LaValle et al., 2011; Davenport et al., 2012; Constantiou and Kallinikos, 2015). Big data, which are large data sets characterised by their diversity, frequency by which they are updated, and their speed of growth (Constantiou and Kallinikos, 2015), are emerging as a new and important phenomenon in the business world.

Davenport et al. (2012) explained that companies wishing to take advantage of big data need to learn how to use real-time data collected through a variety of means such as sensors and radio frequency identification. Such resources and capabilities allow organisations to develop strategic capabilities necessary to have a deeper understanding of the business environment, which in turn help them to create new products and services and to respond to changes in usage pattern in real-time (Davenport et al., 2012; Constantiou and Kallinikos, 2015). Moreover, Davenport et al. (2012) also asserted that these new developments represent a new era of data analysis distinctively different to that of traditional data analysis environments. Consequently, it is clear that big data will have a major impact on various aspects of organisational design and structure. Among these aspects, decision making is an obvious contender for change, where Constantiou and Kallinikos (2015) argued that *"big data reshapes the means and operations through which information becomes available for decision makers in organizations."* (p. 45)

As stated above, decision making can have a direct impact on firm performance. In a study by Citroen (2011), it was evident that the role and value of information in decision making are of prime importance. It was also concluded that some negative aspects of information, such as information overload as well as the constraint of being able to make fast and effective decisions based on large pools of data available for decision makers, present serious challenges for organisations (Citroen, 2011). This last point certainly typifies the increasing difficulties that organisations face in processing the data available to them and consequently making effective decisions.

The present paper aims to study the impact of contemporary business analytics requirements on decision making and firm performance. This paper also aims to investigate the impact of intensive data-driven decision making processes on the overall organisational structure. It is argued that organisational structure will be impacted upon rather severely when organisations shift their attention to focusing on Big Data; for instance, Davenport et al. (2012) stated that among the main steps organisations need to take in order to take advantage of big data is to move *"analytics away from the IT function and into core business, operational and production functions."* (p. 22)

This paper is structured as follows: a literature review aiming to look into decision making and its impact on organizational structure and firm performance. Three case studies are then presented, followed by a findings and discussion section.

Literature Review

Decision Making, Information and Organisational Structure

The literature displays a wide range of studies in the area of decision making. The focus of such research varied immensely from studying the decision making process and its impact on firm performance (Eisenhardt, 1989b; Eisenhardt and Zbaracki, 1992; Nutt, 2008; Shepherd et al., 2015) to even considering aspects such as the impact of emotions (Bachkirov, 2015) as well as intuition (Dane and Pratt, 2007; Salas et al., 2010) on the effectiveness of decision making. In considering the decision making process, the literature covers a variety of views and perspectives. Among these, researchers view such processes either as rationale (Baum and Wally, 2003; Citroen, 2011) or as processes that lack in rationality due to other influencing aspects such as emotions, intuition, politics, and information overload. (Eisenhardt and Zbaracki, 1992; Frishammar, 2003; Dane and Pratt, 2007; Elbanna and Child, 2007; Citroen, 2011; Mitchell et al., 2011) Furthermore, according to Luoma (2016) there are two types of decision making activities: routine decision making and problem solving. The former refers to decision making based on well established procedures, developed over time due to the repetitive nature of the situation in question. Problem solving, on the other hand, refers to making decisions where new or unfamiliar situations occur. Both types differ immensely, where although both types can target highly complex problems, problem solving tends to involve much more uncertainty and ambiguity. (Luoma, 2016; Elbanna and Child, 2007)

According to Baum and Wally (2003, p.1109) a rational decision making process involves several steps; (1) give attention to a problem or opportunity; (2) collect information; (3) develop an array of options; (4) value the options using expected costs and benefits; and finally (5) select the option with the greatest utility. The information aspects of decision making have been of particular interest from researchers across many disciplines (Kuljis et al., 1998; Frishammar, 2003; Citroen, 2011; Van Knippenberg et al., 2015). Although it seems logical that the success of a rational decision making process relies heavily on the quality and completeness of information available to the decision makers, the collection of such information is often limited by time and resources. (Citroen, 2011) Moreover, there is an increasing concern about the continuing explosion of information production and use (Hilbert and López, 2011; Van Knippenberg et al., 2015) which makes the task of collecting appropriate and complete information for decision making an increasingly difficult task. What is, indeed, becoming a challenge for organisations is not the traditional issue of scarcity of information for decision makers, but rather dealing with the all important and tedious issue of information overload. (Van Knippenberg et al., 2015) In this context, attention becomes also a severe problem; although access to data is happening at an unprecedented rate, what seems to be increasingly difficult to acquire is the right and effective attention required for decision makers to process such information. According to Van Knippenberg et al. (2015, p. 650) *"[t]he amount of information scales faster than the attention of human decision makers who have to make decisions about which information has priority, and what will be shunted away."* Furthermore, concepts such as intuition have also come to play an important role, particularly in environments characterized as turbulent. (Dane and Pratt, 2007; Salas et al., 2010) In this context, reoccupation with speed and accuracy of decision making is not new, which was mainly driven by the classic trade-off that *"decision accuracy is often inversely related to decision speed."* (Dane and Pratt, 2007, p. 33) Intuition becomes crucial in such contexts, where decision makers attempt to manage the complexity of a situation they face by relying on their abilities to synthesise information quickly and effectively (Dane and Pratt, 2007).

Organisational structure is also another important aspect when related to decision making. Much research has been done on organisational structure and its impact on firm performance. According to Csaszar (2012) organisational structure is of tremendous importance from an information processing perspective as it controls and determines how *"information flows and is aggregated inside organizations, allowing organizations to accomplish goals that would be otherwise unattainable by any of its individual members."* (p. 616) In this context, organizational structure becomes the means by which boundedly rational individuals collaborate and aggregate the information they produce (Sah and Stiglitz, 1986; Eisenhardt and Zbaracki, 1992; Csaszar, 2012).

Decision Making in Data-Intensive Organisations

Advances in digital technology as well as the savviness of end users have continued to develop rapidly in recent years, leading to more data being generated than ever before. (Hilbert and López, 2011; George et al., 2014; Van Knippenberg et al., 2015) What has, consequently, become more prominent is concepts such as Big Data which are signalling that organisations have to seriously reconsider the way they manage their operations. For instance, Van Knippenberg et al. (2015, p. 650) argued that *"[o]rganizations cannot assume that all this information comes for free; instead, individuals, groups, and organizations must devote substantial financial resources as well as considerable managerial time to developing and implementing strategies and policies to help them make the best use of the information available to them."*

The concept of Big Data is not very clearly, nor accurately, defined, partly because of its novelty. What is becoming clearly evident is that big data is not simply about the bigness of data, but more about the level of sophistication as well as the smartness of such data (George et al., 2014) According to Markus (2015) the consequences of Big Data on organisations are still not fully understood, and there is great potential in researching the area. Davenport and Patil (2012) further argued the lack of data scientists as a serious concern in several sectors such as e-commerce, marketing intelligence, science and technology, public and private health, public security, etc. Moreover, Chen et al. (2012) argue that, unlike traditional data, the big data that e-commerce systems collect from the web is often less structured and contain information on customer opinions and behaviour that are useful for an organisation's decision-making. Barton and Court (2012) propose three areas where organisations need to focus and build strengths in order to improve the performance and benefit from big data and its advanced analytics. Firstly, the organisations have to think of creative ways of sourcing data, i.e., from web analytics, networks, social media, etc., and collate the necessary infrastructure/software to capture, store and analyse data. Secondly, organisations have to understand the critical success factors that are important to their business and build models to predict and optimise performance outcomes. Finally, present the information to the decision makers in user friendly and easy to use tools. The usefulness of data analysis and information depends on how well the results are understood by decision-makers (Hogarth and Soyer, 2015). Consequently, the information collection aspect of a decision making process (Baum and Wally, 2003) becomes even more crucial to the success of such decisions. In this context, Davenport et al. (2012) have argued that organisations should increasingly focus on data flows as opposed to data stocks. The flow of data characterises contemporary business environments in which data is continuously moving across the organisation, and the latter has to capture meanings while the data is flowing. This also leads to the imperativeness for organisations to be ready to gather, analyse and interpret data in a continuous manner, and most importantly be ready make decisions and take action while such a process is taking place (Davenport et al., 2012). This strongly reflects the already well established research on fast decision making in high-velocity and turbulent environments (Eisenhardt, 1989b; Judge and Miller, 1991; Oliver and Roos, 2005; Smith, 2014).

Another important aspect of how current developments in data analytics are affecting organisations, is the need to be consistently agile in discovering valuable information, patterns, and opportunities. (Davenport et al., 2012; Hayashi, 2014; Constantiou and Kallinikos, 2015) This, according to Davenport et al. (2012), will require organisations to completely rethink their assumptions about the interaction between business and IT. Such interaction will often require organisations to move analytics from IT into core business and operational functions in order for them to remain agile by remaining very close to data and its fluctuations. This would be a serious departure from traditionally structured organisations, and is a clear indication of the impact of contemporary decision making requirements on organisational structure. This very consistent with the views of Csaszar (2012) in that organisations need to be able structure themselves in such a way that information flow and aggregation are optimised for accomplishing their goals.

Performance measurement and decision making

It is widely recognised that performance measurement (PM) brings efficiency gains in many organisations (Neely et al., 1995). Nudurupati and Bititci (2005) identified that senior management commitment and drive is essential in making organisations use performance measurement to empower people as well as enhance their improvement culture which will eventually promote proactive decision-making. With the evolution of information technologies, the PMS is enriched with new functionalities which allow enhanced support for decision making within the organisation (Marchand and Raymond, 2008). According to Tsakonas and Papatheodorou (2008), providing open access to performance information will be beneficial to organisations in terms of its usefulness, particularly to enhance decision-making. While the literature support the argument that PM supports decision-making, it is less clear on the nature of this relationship, i.e. which aspects of PM will support what aspects of decision-making (LeRoux and Wright 2010).

Strategy and its implementation through PM has significant impact on people's behaviour and communication that generate necessary organisational capabilities to create competitive advantage (Franco-Santos et al., 2012). The challenging problem for PM in the digital era is that the external environment is not stable and hence organisation's strategy (Bititci et al 2012). Melnyk et al (2014) extends this notion and argue the need for development of a resilient PM approach to reflect strategy in volatile environments. Nudurupati et al (2014) proposed that organisations should take the advantage of technical disruptions to innovate new products, services, approaches or business models. Wamba et al (2015) argue that future organisational performance is closely linked with technological developments in digital economies.

It is evident that advances in technology (such as ICT) supports the performance measurement system throughout its lifecycle, i.e. in designing, implementing and using performance measures for decision-making in improving organisational performance (Bourne, 2005). However in the last decade the advent of technological developments (high speed network connections, web stream data, voice and video data) as well as social media (Facebook, LinkedIn, Twitter, etc.) has grown exponentially. Organisations are dealing with varieties and volumes of data never encountered before (Davenport et al 2012; Chen et al 2012). However, the challenge remains valid for researchers and practitioners to develop resilient performance measurement systems (in dynamic contexts) that present sensible information to enable proactive decision-making (Melnyk et al 2014; Bititci et al 2012).

This study proposes to extend the existing body of knowledge by further investigating the impact of decision making on firm performance by specifically looking into the role that contemporary data analytics play in informing the decision maker as well as shaping organisational structure. The above literature review has given enough indication that organisations need to carefully reconsider their traditional practices if they are to successfully exploit all the benefits that contemporary data analytics has to offer. As such, reconsideration of how data are captured and analysed, how decision making processes are conducted, and how organisational structures are optimised, seems to be a necessity. We propose to conduct the remaining of this paper as an exploratory study with the aim of analysing what the current organisational practices are.

Methodology

This study is exploratory in nature, where the objective is to investigate how organisations should embrace data analytics in their businesses with the aim of improving the effectiveness of their decision making. The main method chosen for this study is a case study approach. A case study approach is desirable in this context as it *"examines a phenomenon in its natural setting, employing multiple methods of data collection to gather information from one or a few entities (people, groups, or organizations)."* (Benbasat et al., 1987, p. 371) Furthermore, we aim to focus on using multiple case studies, which, according to Cavaye (1996, p. 237), *"enables the researcher to verify that findings are not merely the result of idiosyncrasies of the research setting."* Three case studies are used in this research; Food Retail Company (FRC), Tyre Manufacturing Company (TMC) and Ready Prepared Meal Company (RPMC). With regards to data collection, as part of the multiple-case-study approach, several methods of collection are used. As per Yin's (2003) recommendation, triangulation of data is important in order to strengthen its validity. We have run semi structured interviews with key decision makers in the three cases. We also used personal observation and company documentation as a means of triangulating the data. The following is a description of each case independently, consisting in a preliminary within case analysis (Eisenhardt, 1989a).

Findings and discussion

This section is based around establishing a cross-case analysis to complement the within case analysis (presented briefly in the table below) (Eisenhardt, 1989a). The objective is to explore the potential patterns that might emerge from the collected data. With the aim of structuring this analysis, a set of dimensions (Eisenhardt, 1989a) have been used based on the literature review presented above. In studying decision making in data-intensive environments, a few important elements emerged from the literature; a rational decision making process is based on several phases, among which the element of information collection is crucial to its success and effectiveness. This is particularly valid in the current business climate, which characterised by a rapid and almost uncontrollable increase in the amount of data stored by organisations. The first dimension to be used here is that of *"data capturing"*, which looks into how the three organisations (FRC, TMC, and RPMC) capture their data. This also leads us to the second dimension being *"data analytics"* which looks into how the collected data is processed into information suitable for decision making. Moreover, as the literature suggests, organisational structure has a crucial role to play in coordinating and facilitating the flow and processing of information, which in turn affects the decision making process. We see *"organisational structure"* as a mechanism by which a decision making process is facilitated, and thus forms our third dimension for the cross-case analysis. Finally, since the essence of this study is to look into the impact of data analytics on decision making and hence on organisational performance, our fourth analysis dimension is *"organisational impact".* Table 1 presents the four dimensions discussed above across the three case studies, together with the results.

Table 1: Cross-case analysis – Evidence from three cases

	FRC	TMC	RPMC
Background	It is a British food retailer belonging to a group, which has diversified into numerous industries. The food retailer is able to act independently and autonomously from the rest of the group. Their main priority is customer convenience; they nominally compete on price in some circumstances but rarely do they ostensibly use quality to differentiate themselves from their competitors. Their main customers are people in their twenties; generally, as age increases their proportion of each age bracket decreases. Key decision making is centralised, with data at the core of insights. However, to progress further they hope that through data education and the dissemination of relevant information to the appropriate stakeholders that they can empower middle level managers to be their own decision makers.	It is a tyre manufacturing company that produces tyres for a range of vehicles types, from cars and motorbikes through to trucks and agricultural vehicles. The performance of the business is based on five core principles: efficiency (output), cost, quality (zero defects), empowerment of people, and safety. Currently there is a permanent trade-off between output and quality in that higher output is offset by lower quality (or higher waste). The organisation therefore needs to explore innovative ways for increasing economic or manufacturing performance without offsetting other measures. The empowerment of factory workers and the use of data analytics is an area that is receiving more time and financial investment for improved decision making to feedback into superior business practices.	RPMC is a British food production company that specialises in selling ready prepared meals for sale in supermarkets, and a variety of other retailers. Currently, the company is going through a period of rapid and increasing growth. While the company is experiencing exponential revenue growth, serious internal inefficiencies are increasingly becoming a major concern. The pressure brought by this increasing growth led to a higher level of uncertainty making planning almost impossible. Such pressure was also enhanced by the nature of the company's internal systems, based essentially on manual processes and basic spreadsheet-based data records. As such the company made the decision to move away from manual processes, automate some of the production line and bring in an ERP system with the aim of improving the overall performance.
Data capturing	• Very advanced data capturing practices among the three case, nut still encountering difficulties due to software incompatibility. • The company has a high level of awareness of what data needs to be collected. • The company is also into highly sophisticated, and mainly unstructured, data capturing, mainly sourced from social networks.	• The company uses a very structured approach to collecting operational data. • The data, goes through continuous re-evaluation with the aim of improving accuracy. • Data are entered into an in-house system (PCS) which is then accessible across the organisation.	• Very immature data capturing processes, and often crucial operational data, such as stock, are not even recorded. • No immediate access to data since the latter are mainly recorded in locally stored spreadsheets. • Most data is recorded manually. • Data always lagging behind due to lack of real-time data records.
Data analytics (DA)	• High level of awareness in terms of having to prepare and simplify data for the appropriate decision makers. • Difficulty in cross-analysing data throughout the organisation due to the silo effect between departments. • Complex data often requires the assistance of the IT department.	• Lack of sophistication on the data analytics side. Data has to be exported to MS Excel for analysis, which is very inefficient. • Limited analysis is conducted on the data, resulting in less than desirable intelligence being extracted. • Benchmarking across several plants is standard practice.	• Data analysis often based on limited, inaccurate, and incomplete data sets. • Heavy reliance on intuition and manager's experience when analysing data. • Production planning is a very crucial operation and is mostly based on intuition.

Organisational structure	• A fragmented organisation in the form of silos. • The silo structure of the organisation has a clear impact on the flow of data across the different departments. KPIs, as a result, are not common across the organisation.	• Although the collected data is wide spanning, it comes from several plants. The structure of the organisation is well integrated, which facilitates the flow of data. • Scepticism about the accuracy of data that come from the system due to occasional lack of staff supervision.	• Poorly defined roles in terms of data analytics. Managers analyse and interpret data almost on good will. • A very disjointed organisation that is completely overwhelmed by its own success. • Often, decisions are made on a very ad-hoc basis as a reaction to events or problems.
Organisational Impact	DA played a strong role in strategic decision making such as bringing in regional schemes and promotions that have not only increased basket spend but profitability and repeat business. Analysis of operational data is often used to identify poor performance pending further investigation. Structure and culture are all restricting analytical capabilities. Each department has their own KPI's and financial incentives, as such business-improving decisions are second to departmental performance. Departmental objectives may conflict with each other, exacerbated by poor cross function communication and self-serving behaviour, results in decreased performance of overall business objectives. Though strong analytical skills are available, currently data adverse employees, disparate systems and functional silos limit capabilities. FRC want to know their customer's habits more and they are putting into place technology that may help them gather more information regarding their 'known unknowns' However further insight into customer behaviour only if the decision makers are educated in data and willing to accept and incorporate as part of the decision making process.	DA identified problems and used for justification to gain support to influence changes that need to be made. DA is used in conjunction with improvement initiatives and PM to bring change in the processes. Although influence of DA is not high at the moment in identifying and solving issues on a day to day basis, it is normally used to back up management decisions at higher level. This is due to the lack of analytics capabilities of people at lower levels together with inflexible systems that were designed long back. However with the recent development of simulation based decision support tool has demonstrated the capabilities of DA and how it has empowered people and influenced them in their planning decisions. The main barriers for increasing the impact of DA are largely political and historical. As decision making is a top down process, organisational and operational decisions always come from the heads of factories or from the head office. However, the factory is aiming to bring the grassroots' workers closer to the data. Using the aforementioned modelling tools empowered people in redeploying resources in making optimal changes thus improved their planning decisions, which in turn has increased lead-time, reduced waste and output. DA has assisted in identifying the root causes in real-time, which improved the KPI results, increased transparency, empowered employees at lower levels, optimized the resources and inventory.	One of the main uses of DA for decision making is as part of short term forecasting of production needs. Because of the lack of sophisticated data capturing and analytical capabilities, real time decision making is done based on the shift managers' experience. Managers only have autonomy on decision making up to a certain level. Decisions that have an impact across the organisation are made during periodical meetings with the directors. This is the main time in which data is explored in depth. Existing DA clearly demonstrated that the company is growing very fast while labour costs and inefficiencies were both growing in some cases at a disproportionate rate, often because of the ad-hoc workforce brought in to comply with increased demand. There is a realisation that real time production data would be useful so that internal production efficiency improvements would be viable. Truly effective and organisationally integrated analytics are restrictive as the technology facilitates for capturing a wider variety of data is not available yet. However, they are currently hoping to combat some of these issues with more process automation with a suitable ERP system for improved data capturing which can then be more thoroughly analysed. These types of organisational changes are necessary to facilitate more effective data analytics. However current staff education on analytics will need to be invested in as well as hiring more data proficient employees or train the existing employees

Data capturing

The three case studies showed rather different attitudes towards data collection and recording. On one end, FRC and TMC were the most sophisticated in terms of recording and handling data. Both organisations showed high levels of commitment to ensuring that good levels of accuracy and timeliness of data are respected. Although the commitment is there, both cases have serious issues in data handling, mainly caused by the structure dimension which will be discussed subsequently in this section. On the other end of the spectrum, RPMC demonstrates an almost opposite style to the other cases in terms of their handling of data. RPMC is clearly far behind in terms of capturing and storing data, where not only some of the basic operational data, such as stock levels, are not even captured, the transactional data that are captured are recording in an almost ad-hoc way relying mainly on the willingness of some employees to do so. The company has no mechanisms for automating data capturing, although it is working on implementing an ERP system that will potentially play a crucial role in changing and improving this aspect. What is clearly noticeable across the three cases is that organisations with already established mechanism for automating data capturing, have the capacity and the willingness to step their decision making up and move to the next level of sophistication. A good illustration of this is how FRC is attempting to step up their operational and strategic decision making by considering unstructured data collected via social networks. Such level of awareness of the value of data clearly opens up new opportunities for improving the level of sophistication of decision making. Conversely, organisations lacking the basic mechanisms for automating data capturing, such as RPMC, struggle to have a good grasp of the information required for decision making and rely mostly on intuition and experience for making decisions. A good illustration here is how orders are managed at RPMC; due to dynamic nature of the orders they receive, but also due to their lack of sophistication and timeliness in recording data, RPMC essentially predict orders based on the purchasing manager's intuition, which are then readjusted once the orders are received. The latter are often different to the forecast, and sometimes so different that orders cannot be completely fulfilled resulting in wasted opportunities.

Data analytics

This dimension is linked very closely to the previous one, across the three cases. The data capturing dimension proved to have a direct impact on the organisations ability to extract meaningful and useful intelligence. Data from the three cases shows that, for instance because FRC have, relatively, more sophisticated data capturing practices, their focus is essentially on conditioning the existing data by filtering it and presenting it in the right format to decision makers with the aim of facilitating and optimising the decision making process.

> *"People like what they already know" - FRC*
>
> *"Chunks of relevant data are passed down to those that need it with recommendations" – FRC*
>
> *"We try to give them little bits at a time, and over time give them more when they understand what they have" – FRC*

As the level of data capturing sophistication decreases, so does the ability to extract meaningful intelligence from the existing data. As a result, the preoccupation of these organisations becomes focused on finding and retrieving the right data before analysing it, which becomes rather inefficient and time consuming, leaving very little room for in-depth analysis.

> *"Although cycle time data is widely available, as it is out of date, people always question its validity" – TMC*

> *“Manual data entry on the shop floor could be wrong for various reasons, which could lead to data inaccuracy” – TMC*
>
> *“There is scepticism that workers occasionally create stoppage at times when it is not necessary as shift co-ordinators are not always on the shop floor” – TMC*

In this context, the case of TMC, for instance, shows that due to their concerns about the accuracy of some data, due to it being input manually, substantial effort goes into making sure that the data is suitable and adequately accurate in the first place, which often causes issues with the timeliness of the data and hence its usefulness. The case of RPMC demonstrates even more severe issues due to the inadequacy of their data capturing practices.

> *“We make an assumption based of previously produced volumes in the past days; we do not receive forecasts, so we update our assumptions when we get the order. It is a lot of hand working” – RPMC*

The company finds data retrieval so problematic that the bulk of their analytics are mainly based on the managers’ intuition and experience, which seems to have been working to a certain extent so far. However, RPMC’s growth has increased so much that their traditional data analytics are becoming noticeably unmanageable, and the company is finding it increasingly difficult to make even the most basic decisions, which is reaching a rather critical level.

Organisational structure

The third dimension relates to a core concept of this study, where it is argued that organisational structure can have a direct impact on the effectiveness of decision making. Across the three case studies, some interesting findings have emerged. All the three cases demonstrated that organisational structure can have a detrimental impact on the organisations’ ability to capture data and produce sophisticated analytics. The case FRC, for instance, showed that the existence of a silo structure in the company prevented them from extending their relatively sophisticated data capturing and analytics practices to a corporate level; due to the silo structure, KPIs differ from a department to another, and their lack of integration proved that although local analytics were sophisticated, the company was experiencing difficulties in taking a holistic approach to improving their performance. Equally, although TMC had a good level of integration across their business units, their local data capturing was affected by the fact that a good level of supervision was missing which occasionally led to data inputs being occasionally poorly controlled, resulting the data being mistrusted and hence the decision making processes being severely affected at times. Furthermore, the case of RPMC demonstrated that lack of precise role definition led managers to be under constant pressure to do their tasks as well as make decisions beyond their responsibilities. Such a poorly defined organisational structure forced the organisation to be in a reactive mode almost continuously, limiting their senior managers’ ability to think and make decisions ahead of time. The three cases demonstrate, rather firmly, that organisational structure has a direct impact of the effectiveness of the two dimensions “data capturing” and “data analytics”, and consequently a direct impact of the effectiveness of decision making processes.

Organisational Impact

It is evident form the three cases that DA had a varying impact on each of the organisations. The significance of this impact was determined by three aspects as demonstrated in Figure 1. Firstly, strategic intent of using DA, i.e. either achieving performance or improvement objectives. This also determines the second aspect, which is underpinning technological support to capture necessary data, be it numeric data or subjective data. Bititci et al (2012) argue that organisations should have a strategic intent to process such data into meaningful information to enable decision-making. Without a strategic intent, data often becomes obsolete, redundant and resource consuming. Thirdly, the support from senior management in the form of drive and commitment, which is also echoed in literature (Bititci et al., 2006). In the case of FRC and TMC, the senior management were driving and encouraging their employees to use data in their decision-making. For instance, at FRC, the senior management are interested in understanding the customer/consumer habits and their behaviour and are putting the right resources in capturing such information and looking into the ways of developing the evidence based decision-making culture. Similarly, at TMC, empowerment of factory workers and the use of DA is an area that is receiving more time and financial investment for improved decision making to feed into superior business practices. In contrast, at RPMC (due to its evolving nature), the senior management has recognised the strategic need for DA and hence in the process of sourcing sophisticated data capturing system.

> *"Top level management are advocates of increased data usage for decision making and an active drive towards it is necessary for increased success" – FRC*

> *"We embarked on a partnership with University in developing a decision support tool to help people in forecasting and planning activities" - TMC*

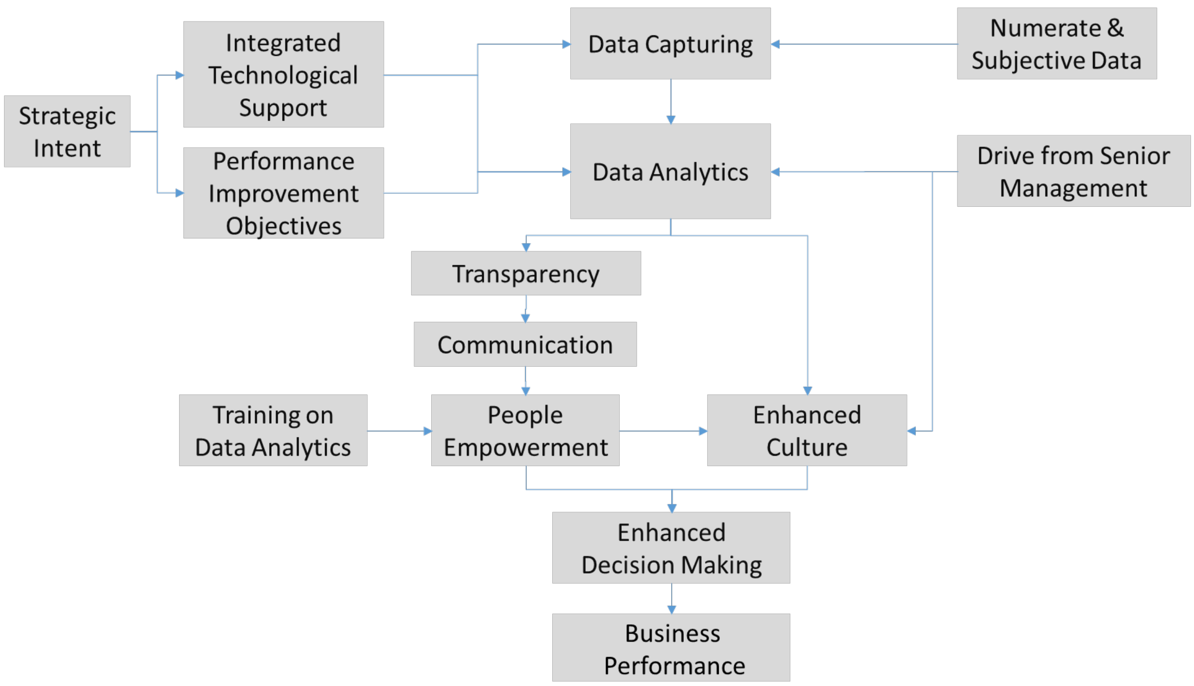

Figure 1: Impact of DA on Organisations

At FMC, DA plays a significant role in terms of processing data to support decision-making. The information is communicated to the people who need it, which creates transparency and empower people to some extent. However, they also highlight the current issues such as their disparate systems, data adverse employees as well as their functional silos, which are restricting the organisation from getting full potential of DA. At TMC, DA plays an important role at senior level in supporting their decision-making. Standard information is available on the intranet with the appropriate access to different employees. This creates transparency in the organisation. Ad-hoc information requests can always be made to the IT team when required, which will be approved through usual channels (often bureaucratic). They also developed decision support tools for improving their planning and forecasting decisions on day-today basis as well as predicting future performance to support long-term decisions.

However, the data accuracy issues, top-down decision making (lack of empowerment) structure and data adverse employees are restricting the organisation from gaining full potential of it. At RPMC, in contrast, the DA is weak or not significant and the employees are making intuitive decisions. They do not have sophisticated data capturing systems and majority of it is manual with some input into spreadsheets. Hence, data is often locked in people's desks with restricted access and no transparency. In addition, employees are data adverse and are always busy in day-to-day jobs and make decisions intuitively.

> *"We try to give them little bits at a time, and over time give them more when they understand what they have. Definitely, data education improves acceptance" - FMC*
>
> *"Powerful data analytics is not always sufficient to bring good outcomes, it is the culture and the political factors that play a key role in making organisations realise the real potential of it" – TMC*
>
> *"We make assumptions based on past experience. We do not have accurate forecasts, so we update our assumptions when we get the actual order. It is a lot of hand working" - RPMC*

It is evident from the three cases that DA communicates data into a more meaningful information to enable decision-making. It is also clear that information should be more openly available to all employees who need it to create transparency and empowers them. It is also essential that employees should be trained on DA to overcome their resistance and enable data based decision-making. This is also echoed by Davenport and Patil (2012) who argue the dearth of data scientists as a serious concern in several organisations. It is the senior management who should take the initiative in driving the culture of employees making autonomous decisions based on evidence.

It is evident that at FMC, DA demonstrated significant impact on senior management's decision making and enhanced better understanding of their customer behaviour, enabled targeted sales promotion, increased sales and profitability. At TMC, DA demonstrated significant impact on both senior management and lower level management decision-making thus improving optimised resource utilisation, increased efficiency and effectiveness, increased production as well as optimized inventory. In contract, at RPMC, lack of DA demonstrated that managers are making intuitive decisions based on experience rather than evidence. This resulted in poor efficiency and effectiveness of their resources and processes.

Conclusion

This paper has presented a very topical area of research, that of data analytics in data-intensive organisations. After looking into three quite distinct case studies, this paper puts forward several propositions; to begin with, it is clear from the three cases that organisations can find themselves at varying stages in their awareness as well as exploitation of data analytics in their daily as well as strategic activities. The three cases above display very strongly the impact of such varying stages on the overall performance. In essence, such performance is driven by the organisation's strategic intent, which leads to establishing a clear path for capturing data and extracting meaningful and useful analytics, which eventually would have an impact on the potential to gain and sustain competitive advantage. The case of RPMC typifies those organisations that have failed to establish such a relationship, resulting in a rather chaotic situation leading the organisation to be very reactive and lacking in strategic direction. Moreover, we re-echo Davenport and Patil's (2012) arguments that nurturing data scientists will increasingly become fundamental to organisations' success in a contemoorary business environment often characterised as fast-paced and data-intensive. However, we would like to argue that having desirable data scientists is only part of the requirements as these need to find themselves in optimal conditions to be able to contribute effectively. An important outcome of this research is that organisational struture is clearly a component of major importance for realising the benefits of data analytics. The three case studies all

displayed shortcomings in their structure that impede the effectiveness of their data analytics practices and the resulting decision making processes. Not only does organisaitonal structure play a vital role in enabling data analytics practices, but also the role of senior management in driving these practices as well as empoering data scientists is of prime importance.
This study has some limitations without which the results could have been even better. Data was collected for three cases, which have well informed this research. However, a much larger data set would have been ideal for strengthening the identified patterns. Moreover, although decision making is of core focus, this research has not explored the element of success of decision making; due to the limited scope, this research has considered the enablement of decision making without evaluation of the resulting outcomes of such decisions. In light of these limitations, we propose a few ideas for future research. Firstly, we suggest that these results should be further considered using a larger data set, perhaps by even aggregating these by sectors, organisational size or other attributes. Furthermore, it would be natural to extend the current research by not only looking into the impact of data analytics on decision making enablement but also by exploring the link between the dimensions discussed above and the success of decision making (managerial or strategic).

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