Performance measurement in data-intensive organizations: resources and capabilities for decision-making process

Abstract. Many organisations are increasingly dealing with massive amounts of data to face new competitive challenges. However, even if powerful technologies support data collection and analysis, the lack of appropriate resources and capabilities for handling socio-technical systems often hinders effective decision-making. Hence, this study aims to investigate how performance measurement systems should develop and drive appropriate resources and capabilities to enable effective decision-making for creating a competitive advantage in data-intensive organisations. A case study approach was adopted with seven data-intensive organisations using one-to-one semi-structured interviews, personal observation, and secondary sources such as company documentation, meetings notes, reports, etc. The findings highlight the relevance of organisational structure and cross-functional communication to cultivate senior management commitment and drive to develop data capturing and analytical capabilities to support effective decision-making. The findings also suggest that to enable superior data capturing capability, organisations should leverage on a higher degree of automation, a higher degree of awareness on data value, and data variety for providing accurate and timely information as well as developing new business insights. Similarly, to enable superior data analytics capability, organisations should develop analytical skills, data visualization, and data-driven culture to make effective decisions.

Keywords: Performance measurement, decision-making, organisational structure, data capturing, data analytics, resources and capabilities, competitive advantage.

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Introduction

While studies focusing on business performance measurement in strategic and operations management research abound, the theme of decision-making frequently emerged as one of the most important factors influencing organizational success (Csaszar, 2012; Ji-fan Ren et al., 2017; Al-Surmi et al., 2021; Awan et al., 2021). On one hand, the literature underlines the need to revise managerial processes in general, and decision-making in particular, to face the current VUCA world, i.e., conformed by the features of volatility, uncertainty, complexity, and ambiguity where priorities change, information is unreliable, and results are difficult to predict (Bennett and Lemoine 2014 Minciu et al., 2020). On the other hand, insufficient attention is given to the resources and capabilities that complement the decision-making process (Awan et al., 2021). The focus of such literature varies, where some studies were more concerned with the decision-making process and its effectiveness (Elbanna and Child, 2007; Awan et al., 2021) whereas others were more interested in the impact of decisions on business performance (Baum and Wally, 2003; Gunasekaran et al., 2017; Al-Surmi et al., 2021). Particularly, studies looking into the speed of decision-making attempted to research the impact of fast decisions on business performance (Oliver and Roos, 2005; Baum and Wally, 2003; Netz et al., 2020). Most of this research 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; Melnyk et al., 2014).

Wamba et al. (2015) argue that performance measurement is closely interlinked with technological developments in digital economies and highlights the urgent need for more empirical research. 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 such data (LaValle et al., 2011; Davenport et al., 2012; Constantiou and Kallinikos, 2015; Awan et al., 2021). 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; Tan et al., 2017; Tang and Liao, 2021), are emerging as a new and important phenomenon in the business world (Fatorachian and Kazemi, 2018; Tang and Liao, 2021). Davenport et al. (2012) argue 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 organisations require necessary resources and capabilities (such as analytics) to have a deeper understanding of the business environment, which in turn helps 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; Gupta and George, 2016). Some researchers pointed out that the positive impact on the business performance and success of the organisation depends on the level of data analytics capability they possess (Kamble and Gunasekaran 2020; Ferraris et al., 2019). Nudurupati et al. (2016; 2021) argue that in a digital economy, organisations need to position their performance measurement systems (PMS) to both define the strategic intent for data as well as drive the data analytics to demonstrate the trends in business performance to enable effective decision-making. 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 (Klein, 1998; Citroen, 2011; Nudurupati et al. 2016; Netz et al 2020).

This study poses the following research questions:

1. What are the main resources and capabilities that enable decision-making in data-intensive organizations?
2. How should PMS drive resources and capabilities that complement the decision-making process for creating business impact?

Hence the overall aim of this study is to understand how PMS should drive appropriate resources and capabilities to enable effective decision-making for creating competitive advantage. Resources are studied as "*stocks of available factors that are owned or controlled by the firm [that can* *be]…converted into final products or services by using a wide range of other firm assets and bonding mechanisms such as technology, management information systems, incentive systems, trust between management and labour, and more*" (Amit and Schoemaker 1993, p. 35). Capabilities are *"a firm's capacity to deploy resources, usually in combination, using organizational processes, to effect the desired end. They are information-based, tangible or intangible processes that are firm-specific and are developed over time through complex interactions among the firm's Resources"* (Amit and Schoemaker 1993, p. 35). The main drive behind this research is the opportunity that is presented in the current business climate in the form of a dramatic increase in the pace of data handling and processing necessitating a rather different approach from organisastions. There is a very evident gap in that decision-making is becoming increasingly difficult to apply using traditional tools and approaches. This research aims to help narrowing the gap by identifying the key aspects that organisations need to address to adapt to such fast-paced environments for effective handling socio-technical systems.

This paper is structured as follows: a critical review of key literature aiming to look into performance measurement systems and their association with decision-making, as well as a capabilities perspective within the context of data-intensive organisations. This is followed by the description of the methodology used to achieve the overall aim. The findings and cross-case analysis are then reported and subsequently discussed. The paper closes with the conclusion and directions for further work.

Literature background

Performance measurement and decision-making.

The literature widely recognised that performance measurement has a huge impact on decision-making processes (Grafton et al., 2010; Franco-Santos et al., 2012; Nudurupati et al., 2021) be it, financial or non-financial decisions (van Veen-Dirks, 2010). Since the mid-1980s, PMS has been recognised as a balanced and dynamic system supporting the decision-making process by gathering, elaborating and analysing information (Neely et al. 2002). PMS supports making decisions at all hierarchical levels (Braz et al., 2011). Strategy and its implementation through PMS have a significant impact on people's behaviour and communication that generate necessary organisational capabilities to create competitive advantage (Franco-Santos et al., 2012; Smith and Bititci, 2017).

In 2010, Akyuz and Erkan (2010) underlined the need to identify the application of PMS for decision-making and control at an operational level. A few years later, Moreira and Tjahjono (2016) proposed a conceptual framework that used performance measures as the main driver of the decision-making process within the supply chain, with particular attention to the operational level. Kache and Seuring (2017) identified 43 opportunities and challenges linked to the emergence of Big Data Analytics (BDA) from a corporate and supply chain perspective. Gölzer and Fritzsche (2019) and Sheng et al. (2017) underlined a growing awareness of big data's business values and managerial changes led by the data-driven approach. Raffoni et al. (2018, p. 64) described the potential of business performance analytics in overcoming the lack of strategic focus and the *"limited ability to quantify the cause-effect relations between value drivers and firm performance"*. Several papers explored the impact of BDA capabilities could develop the ability to manage not only the customers' performance by enhancing the decision-making processes (Dahlbom et al., 2020; Shet et al., 2021) but also human resource, financial, operational and supply chain performance management (Talwar et al., 2021; Sardi et al., 2021). Shet et al. (2021) identified the challenges that hinder human resource analytics (HRA) practices and developed a framework to explain the factors that impact HRA adoption within organizations. Hallikas et al. (2021) highlight the positive and significant relationships among digital procurement capabilities, data analytics capabilities, and supply chain performance. In particular, the authors point out that digital procurement capabilities mediate the positive relationship between external data analytics capabilities and supply chain performance.

Bititci et al. (2012) highlight that the challenging problem for PMS in the digital era is that the external environment is not stable thus impacting organisations' strategies. Melnyk et al. (2014) extends this notion and argue the need for the development of a resilient performance measurement approach to reflect strategy in volatile environments. Emerging technology supports the implementation of PMS with increased data accuracy and flexibility in decision-making processes (Grafton et al., 2010; Pavlov and Bourne, 2011). In the last few years, technology is often described as one of the key contingency factors in PMS implementation and use (Sardi et al., 2020; Nudurupati et al 2021). Garengo et al. (2007) point out that on one hand, advanced Information Systems (IS) is essential to creating a favourable context for implementing and using PMS. On the other hand, the benefits highlighted by PMS implementation and use promote further investment in IS. Koufteros et al. (2014) illustrate that diagnostic use of PMS leads to improved capabilities, which can impact on organisational performance. It particularly happens when appropriate feedback mechanisms are in place and able to support decision-making. In fact, constructive feedback influences decisions and supports managers in translating strategy into operational activities (Matthias et al., 2017)

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; Devi and Ganguly 2021; Tang et al., 2021; Huang et al., 2020). Kaplan and Haenlein (2010) investigated the potential contribution of data collected by social media in decision-making processes, delineating the need for resources and capabilities for PMS. Recent studies investigate the impact of the use of social media on PMS technical features, paying particular attention to indicators and measurement processes, and the use of these indicators within business processes. They found that there is poor understanding of the need for integration between the social system solutions and the entire performance measurement system (Sidorova et al. 2016; Arnaboldi et al. 2017; Sony and Naik, 2019; Huang et al., 2020). Sardi et al. (2019) highlighted that enterprise social networking could support the development of a holistic PMS as it provides real-time data collection, analysis and reports that encourage democratic and participative performance management and, at the same time, it facilitates relationships and knowledge sharing useful to the effective use of performance information. Despite the high potential of social system tools, they are mainly used for communication and marketing purposes and the data from it is rarely used by other business functions (Al-Surmi et al., 2021; Huang et al., 2020; Tang and Liao, 2021). 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; Nudurupati et al 2021).

Performance measurement and BDA

A number of literature reviews and empirical investigations (Mishra et al., 2018; Kamble and Gunasekaran, 2020; Rasool et al., 2021; Kamble et al., 2020) identified sets of indicators and criteria that organisations can use to evaluate BDA capabilities and tried to give a holistic view of big data and performance measurement, with particular attention to data quality (Hazen et al., 2014; Batini et al., 2015; Kwon et al., 2014). Kamble and Gunasekaran (2020) identified two main dimensions for evaluating the level of business data analytics capability, which are quality and time. Under the quality dimension, Kamble and Gunasekaran defined 15 capabilities (i.e., the analytical tools skill-set, business domain knowledge, connectivity, control, co-ordination, data currency, data accuracy, data completeness, data-driven culture[1], data format/consistency, relational domain knowledge, reliability, security and privacy, technical domain knowledge, top management commitment, volume of data). Under the time dimension, they focused on real-time data and response time capabilities (Kamble and Gunasekaran, 2020). Verma et al. (2021) identified five main quality criteria named accuracy (i.e., the value to the degree of proximity), completeness (i.e., sufficient information to describe), consistency (i.e., values must be consistent in a database), timeliness (adequately up-to-date), validity (values of data are consistent with their domain) and uniqueness (i.e., one instance to be displayed in the database). Sardi et al. (2021), report the emergence of new performance

[1] Using data and analytics in decision making at various levels of organisations

measurement practices (such as continuous knowledge sharing, collaborative performance management, challenging and fun management, learning and motivating management and self-performance management) based on increasing use of predictive and social analytics and their huge impact on the ability to provide insights based on data-driven decision-making processes. Ferraris et al. (2019) underlined that the organisations with higher BDA capabilities, both technological and managerial, increased their performances.

The main motivation favouring investments in developing BDA capabilities is the improvements in their decision-making processes. However, despite the potential of BDA to improve performance measurement systems, its real impact is still not entirely clear (Mello and Martins 2019). Lacking skills in analytics and business understanding, inability to go beyond reporting, misconceptions related to big data and traditional compliance-oriented HR culture, pose important challenges for the data analytics capabilities (Dahlbom et al., 2020).

According to Wamba et al. (2017) BDA provides organisations with massive opportunities by allowing them to be more proactive. As argued by Janssen et al. (2017), since BDA requires the collaboration of multiple entities internal and external to the organisation, the quality of decision making is not only reliant upon the quality of data but also on the quality of data collection processes as well as the manner in which data is processed. Therefore, aspects of business process integration and data flow are of prime importance (Themistocleous and Corbitt, 2006; Mani et al., 2010). Constantiou and Kallinikos (2015) also note that due to the vastly different nature of data that is now processed by organisations, mainly characterised by its lack of structure and unpredictability, is often difficult to fit with existing tools. It is, therefore, imperative for organisations to be able to develop the ability to interpret such data in a timely manner in order to maximise its positive impact on decision making (Baesens et al., 2016; Constantiou and Kallinikos, 2015; Müller et al., 2016).

The decision-making process.

In considering the decision-making process, the literature covers a variety of views and perspectives (Nutt, 2008; Shepherd et al., 2015; Mello and Martins, 2019). Amongst these, researchers view such processes either as rational (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; 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. The first step starts with the formulation of a problem or spotting an opportunity. The next phase in the process involves the collection of the information necessary for the evaluation of the problem or opportunity. Next is the development of an array of options, then value the options using expected costs and benefits. Finally, selection of the option with the greatest utility. When considering the model depicted by Baum and Wally (2003), there are noticeable considerations that are idiosyncratic to contemporary data-intensive organisations. Essentially, what seems evident is that due to the fast-paced flow of data through organisations (Davenport et al., 2012; Papadopoulos et al 2017; Chavez et al., 2017; Netz et al., 2021), spotting problems and opportunities is strongly dependent on good data flow management. Thus, organisations must be able to manage the flow of data in a manner that allows minimising the loss of opportunities. This is a very specific characteristic of current fast-moving, data-intensive organisations. As a result, Baum and Wally's (2003) model can be further expanded by recognising the need for effective data flow management as a prerequisite for spotting problems and/or opportunities, as depicted in Figure 1.

The Capabilities Perspective.

In the current business environment where organizations need to manage a large amount of data to support an ever-faster decision-making process, resources and capabilities supporting the collection and analysis of a large amount of data are recognized as essential for achieving competitive advantage (Constantiou and Kallinikos, 2015; Baesens, et al., 2016). According to Black and Boal (1994, p. 132) *"strategy formulation starts properly, not with an assessment of the organisation's external environment, but with an assessment of the organisation's resources, capabilities, and core competencies".* This is not to say that the external environment bears no importance, but to hint at a new direction that researchers started taking, consisting of a focus on resources and capabilities as a source of competitive advantage (Penrose, 1959; Wernerfelt, 1984; Helfat and Peteraf, 2003, Teece, 2007; Helfat and Peteraf, 2015). Although the capabilities view of the firm has seen tremendous developments in recent years, its core foundation still revolves around a set of fundamental assumptions (Awan et al., 2021). Firms, within an industry (or group), may be heterogeneous with respect to the strategic resources they control, and that these resources may not be perfectly mobile across firms, and thus heterogeneity can be long-lasting (Barney, 1991). Moreover, an important development in the capabilities perspective is that such resources and capabilities can be dynamic and *"involve adaptation and change, because they build, integrate, or reconfigure other resources and capabilities"* (Helfat and Peteraf, 2003, p. 997). Barney (1991) highlighted that not all firm resources and capabilities are strategically relevant, but strategic resources are those that enable a firm to conceive of and implement strategies that improve its efficiency and effectiveness. Such strategic resources and capabilities are characterized by a set of attributes that distinguish them from other non-strategically relevant ones. Such resources have to be valuable, rare, imperfectly imitable and imperfectly substitutable in order for a firm to conceive of and implement strategies that lead them to achieve and sustain competitive advantage (Wernerfelt, 1984; Barney, 1991; Peteraf, 1993). This perspective has gained tremendous popularity in management research due to its usefulness in viewing organsiations as a bundle of resources and capabilities (Barney, 1991), which vary in their strategic value. The adoption of the capabilities perspective in this paper is mainly as a theoretical lens with the aim of structuring and focusing the research contributions.

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, resources and organisational issues (Citroen, 2011). Moreover, there is an increasing concern about the continuing explosion of data 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 tedious issue of information overload (Van Knippenberg et al., 2015).

The usefulness of data and information depends on how well it is presented to and understood by decision-makers (Hogarth and Soyer, 2015; Awan et al., 2021). Consequently, in the decision-making process, the ***data capturing*** becomes even more crucial to the success of such decisions (Baum and Wally, 2003; Guimaraes and Paranjape, 2021). 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 to 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; Oliver and Roos, 2005; Smith, 2014; Netz et al. 2020;).

In addition to data capturing, ***data analytics*** is also recognized as an essential capability. Data analytics are affecting organisations and they need to be consistently agile in discovering valuable information, patterns, and opportunities (Davenport et al., 2012; Hayashi, 2014; Constantiou and Kallinikos, 2015). Mikalef et al. (2021) explore how different inertial forces during deployments of big data analytics hinder the emergence of dynamic capabilities. By disaggregating dynamic capabilities into the underlying capabilities of sensing, seizing and transforming, they indicate that different combinations of organizational inertia hamper the formation of each type of capability. 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.

Organizational capability is described as one of the most relevant sources of competitive advantage (Barney, 1991; Mu et al., 2022). As highlighted by Grant (1996), the growing innovation and diversity of competitions stimulate firms to pay attention to their organizational capabilities, particular on ***structure capability***. Since the 1950s, March and Simon (1958) have highlighted the strong relationship of decision-making with organizational structures, arguing that an organisation's structure imposes *"boundaries of rationality"*. The structure is able to mitigate the cognitive limitation of the organizational members and, even the cognitive limitation of members, supporting the achievement of *"organizationally rational outcomes"* (Simon 1975). Numerous scholars (Jelinek, 1977; Duncan, 1979; Bobbitt and Ford, 1980) have argued the impact of structure on decision-making. 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 rationally bounded individuals collaborate and aggregate the information they produce (Eisenhardt and Zbaracki, 1992; Csaszar, 2012).

The model depicted in Figure 1 demonstrates that data-intensive organisations do present distinctive characteristics, particularly in the way data flows and its consequences on the rest of the decision-making process. It is evident from the literature that the decision-making process, in this context, is much more challenging to operate successfully, particularly because of its dynamic nature mainly due to the constant flow of data (Davenport et al., 2012). As a result, it is only natural that organisations need to adapt to these changes and develop the required resources and capabilities necessary to operate their decision-making processes.

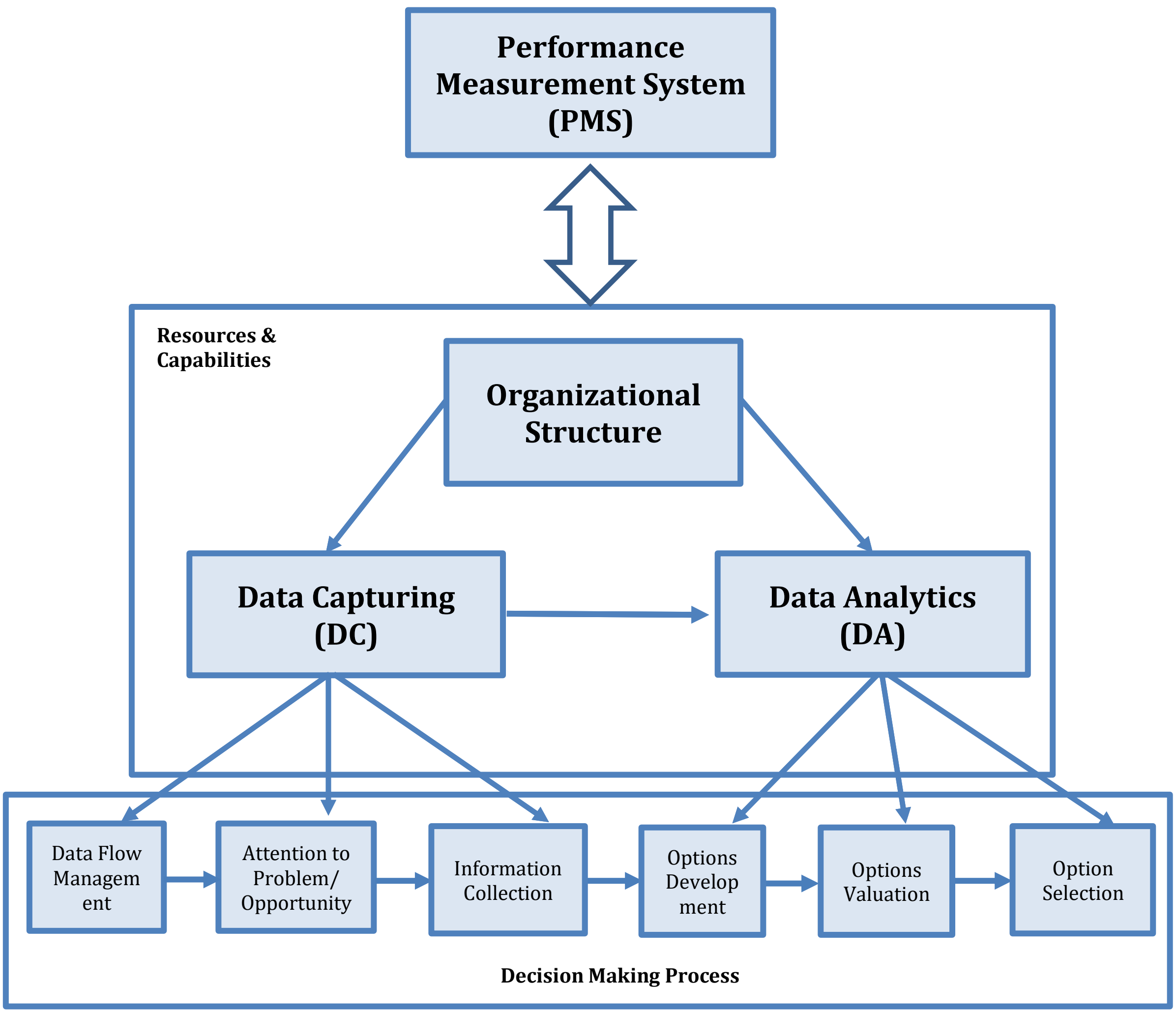

Figure 1 Analytical framework for studying the impact of PMS on resources and capabilities to support the decision-making process

The three primary resources and capabilities emerged from the literature review – i.e., data capturing capabilities, data analytics capabilities, and organisational structure capability. The empirical investigation aims to explore the main factors a data-intensive organisation should develop to ensure effective PMS for completing each phase of the deliberate decision-making process depicted in Figure 2.

Methodology

This study is exploratory in nature (Eisenhardt, 1989). The research method chosen for this study is a case study approach. This method 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 organisations)"* (Benbasat et al., 1987, p. 371). Furthermore, the focus is 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*."

The analytical framework presented in Figure 1 was used in developing the overall research design that has guided both data collection and analysis which is depicted in Appendix A.

In selecting the unit of analysis (UoA), the focus was on leading data-intensive organisations ranging from manufacturing, retail, and service sectors, and distinguished for their high financial performance in the last 3 years. To qualify as a data-intensive organisation, it either needs to process at least 5TB worth of transactional data or deploy at least 10% of its IT investment in data management technology. Within these criteria, to ensure data saturation, seven significant case studies were selected out of expediency of the authors, where they already have established links to access data and are suitable for ensuring the appropriateness and richness of the data collected. As Yin (2018) highlights in case study research, the sampling strategy should be less concerned with the size but more about the appropriateness and richness of the collected data.

Moreover, to further ensure data saturation, the researchers carried out a wide number of interviews. This is in line with Guest et al. (2006)'s recommendation that at least twelve interviews should be conducted to ensure data saturation, while Creswell (2013)'s paper suggests twenty to sixty interviews for reaching data saturation. The profile of the seven companies selected for this research is synthesized in Table 1.

Table 1 Profile of the seven cases and the selected participants for the interviews

Case	Description	Participant job role	Length of the interview
C1	It is a British food retailer belonging to a group, which has diversified into numerous industries. C1 is able to act independently and autonomously from the rest of the group.	Managing Director	1 X 1 hours approx.
		Operations Manager	5 X 1 hours approx.
		Marketing Manager	1 X 1 hours approx.
C2	It is a UK based tyre manufacturing company that produces tyres for a range of vehicles types, from cars and motorbikes through to trucks and agricultural vehicles.	Managing Director	1 X 1.5 hours approx.
		Operations Director	3 X 1 hours approx.
		Operations Manager	5 X 1 hours approx.
		HR Manager	1 X 1 hours approx.
C3	It is a British food production company that specialises in selling ready prepared meals for sale in supermarkets, and a variety of other retailers.	Financial Controller	1 X 1.5 hours approx.
		Operations Manager	1 X 1 hour approx.
		Production Manager	1 X 1.5 hours approx.
C4	It is a UK based company which describes itself as a marketing and digital services company; that provides services for both B2B and B2C customers. Their services range from one-off data requests to many years of marketing and digital support for all their client's needs.	Managing Director	1 X 1.5 hours approx.
		HR Manager	1 X 1.5 hours approx.
C5	It is a British company providing support services to energy companies. It is a limited company, which is owned by a shareholder who is involved in the running of the business. The company has grown massively over the past decade, going from a few hundred employees to a few thousand. Its services include metering services, business and management solutions.	Operations Director	2 X 1.5 hours approx.
		Sales Manager	2 X 1 hour approx.
		HR Manager	1 X 1.5 hours approx.
C6	It is an Italian company established in 1949 to produce shoe polish. About 20 years, ago the ownership started a change management programme in both business models and information management practices. It is a leader company in domestic and professional products such as waxes and detergents.	MD/ son of the founder	1 x 1.5 hours approx.
		Sales / customer manager	2 x 1 hours approx.
		HR manager	3 x 1 hours approx.
		IT managers	2 x 1.5 hours approx.
		Marketing managers	1 x 1.5 hours approx.
		External consultant	1 x 1.5 hours approx.
C7	It is an Italian company established at the end of the 1800s offering traditional furniture. At the end of the 1990s, after a change in the managerial team, business model and organisational approach were revised. Its new business model started offering a mix of innovative modular products and strong core company's values.	MD/ son of the founder	2 x 1 hours approx.
		Production director	3 x 1.5 hours approx.
		HR manager	2 x 1.5 hours approx.
		Accounting manager	1 x 1.5 hours approx.
		Marketing / social managers	1 x 1.5 hours approx.
		External consultant	2 x 1 hours approx.

With regards to data collection, as part of the multiple-case-study approach, three methods of data collection were used. Firstly, one-to-one semi-structured interviews with a cross-section of employees from both senior and middle management (decision-makers) were conducted across the seven organisations. The summary profile of participants and the length of the interviews are depicted in Table 1. The protocol included elements of both focused and semi-structured interviews (Merriam, 1998; Yin, 2018). As more than one author collected the data, an interview protocol was developed to retain consistency across the interviews as well as to avoid personal prejudice. Secondly, personal observations were captured by the authors (on this project), who already had experience of working with the case organisations in various capacities. Each researcher was asked to document a storyline for their case organisation using the interview protocol. Each story was validated with some of the key informants. Thirdly, company documentation, such as reports, copies of visual charts, organisational charts, process maps, etc., were collected across the organisations. As per Yin's (2018) recommendation, triangulation of data is important in order to strengthen its validity. Hence, all three sources of data collection were used as a means of triangulating the data. Following Eisenhardt's (1989a) guidelines, preliminary within-case analysis approach was applied. With the aim of structuring this analysis, a set of dimensions (Eisenhardt, 1989a), i.e., organizational structure, data capturing and data analytics have been used based on the literature review presented above as well as the within-case analysis. Then, the study has also carried cross-case analysis using Yin's (2018) analytical techniques. Each case is initially analysed independently by each researcher and then a number of group sessions were organised to share and discuss the empirical data to ensure the integration of all available data collected from interviews, observations, and documents for consistency in the analysis. This approach took a long time, but it ensured high consistency in data analysis. Despite the strengths and applicability of software analysis, the researchers did not use them in this study as they felt unsuitable for integrating data collected by different sources. Moreover, recent research highlighted weaknesses of software like Nvivo, for instance, data analysis could be subjective as researchers' bias may precipitate in manual coding (validity), where reliability could be compromised (Sanusim 2019; Dollah et al., 2017). Software does not perform an independent rational process or substitute the analyst's interpretative capabilities. There is a danger that qualitative researchers consider the descriptive thematic coding of data to be the end of the project and fail to interpret the data adequately (Denzin and Lincoln2005). Moreover software, like NVivo, requires the user to maintain the hierarchical node structure to explore relationships under different contexts. If this is not maintained, relationships between data can be skewed (Altmann 2013).

Findings

The data was analysed using the framework presented in Figure 1, i.e., three capability perspectives extracted from literature: data capturing, data analysis and organizational structure, to identify appropriate resources and capabilities for effective decision-making. Table 2 summarizes the main empirical findings, which are discussed below. It is imperative to further stress on the fact that the capabilities perspective was used in this paper only as a theoretical lens to guide the authors' thoughts.

Table 2 Cross-case analysis: evidence from the seven cases

	C1	C2	C3	C4	C5	C6	C7
Data capturing (DC)	• Very advanced data capturing practices, but still encountering difficulties due to incompatibility. • The company has a high level of awareness of what data needs to be collected based on measures. • The company is also into highly sophisticated and unstructured data collection mainly sourced from social networks. • High level of awareness in terms of having to prepare and simplify data for the appropriate decision-makers.	• The company uses a very structured approach in collecting operational data based on required operational metrics. • The data go 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. • Collecting non-numeric data to understand customer needs	• 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. • Data always lagging behind due to a lack of real-time data records.	• Collects data with strategic intent, based on a brief provided by the management. • Able to capture data in a range of structures from numerous sources, as well as non-digital data, which is digitised and aggregated. • Internal metrics are used to capture data in real-time.	• The company has an ad hoc approach to collecting data for use. • Most data are captured automatically by their systems. However, data is stored on disparate systems that do not integrate. • Manual input, which is periodic, and needed to update some data repositories. Hence it needs logical validation.	• The company invested in a structured approach to collect data automatically high amount of data variety related to customer, production processes and financial performance and that feed a balanced PMS • Consultation to wide number of people are ensured by advanced electronic devices • The data collection process was redesigned to ensure that data is consistent with the effective company's needs. • Data is collected by an ERP system and social network tools.	• Plenty of data is gathered automatically in external environment and various departments by ad hoc managerial software. • Data is then integrated from different systems including social media platforms, however, the data integration process is not complete. • Control managers are engaged to integrate data collected from different sources and support employees (when needed).
	Quotations: *"We need data from social media to understand our customers"* - *C4* *"The automation of the collected data was essential to improve the process, we will continue to invest to make the collection process even faster and more timely – C6* *"People like doing interesting things when it comes to data… our control managers are constantly working to bring that interesting bit to the forefront"* - *C7*						
Data analytics (DA)	• Difficulty in cross-analysing data throughout the organisation • Need for integration of DA • Complex data often requires the assistance of the IT department.	• Lack of sophistication on the DA. Data has to be exported to MS Excel for analysis, which is very inefficient. • The limited analysis is conducted on the data, resulting in less than desirable intelligence being extracted. • Benchmarking across several plants is standard practice.	• DA 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.	• DA is constant, cyclical and changes based on client needs. • Diverse data sets require numerous software, including from online and 3rd party. • Weekly training is outsourced and tailored to the ability of groups of employees, designed to improve analytical skills.	• DA is underutilised, as there is no strong emphasis on its importance. • Over-reliance on the experience of high-level management and the owners experience stifling. • DA is used reactively, and its proactive use is undermined and overlooked.	• Data from ERP is merged with data collected by different systems and made available online using BI. • Particular attention is given to the visualization of information. • Users are involved in the definition of the visual structure of the data and create their own graphs and reports. • Multi-disciplinary team used DA to identify the key customers that deserve higher discounts	• Control managers offer support in the activities of data elaboration, report generation, creation of visual presentations of the data. • Few persons have skill for data analytics • Posters or other visual graphs are also created and hanged on the wall of each department as well as used during weekly operational meetings and strategic discussions.

<table>
<tr><td></td><td colspan="7">Quotations:
"We try to give them little bits at a time, and over time give them more when they understand what they have" - C1
"Improving data collection and analysis is not a choice, to operate in the international market, we had to invest to acquire the necessary skills" - C6
"We are very reactive in our approach to business analytics" - C5
"We use billboards to visually communicate key information to the employees" - C7
"We make an assumption based on 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"-C3
"We embarked on a partnership with University in developing a decision support tool to help people in forecasting and planning activities" - C2</td></tr>
<tr><th></th><th>C1</th><th>C2</th><th>C3</th><th>C4</th><th>C5</th><th>C6</th><th>C7</th></tr>
<tr><td rowspan="2">Organisational structure</td><td>• A fragmented organisation in the form of silos.
• The silo structure of the organisation has a clear impact on the flow of data across different departments.
• Managers only have autonomy in decision making up to a certain level.</td><td>• Bureaucratic and silo structured organisation with decisions often top-down.
• The company has restricted access to business and sales data.
• The structure of the organisation is well integrated, which facilitates the flow of data upwards for decision making</td><td>• A fragmented silo structured organisation completely overwhelmed by its own success.
• Decisions are often made on an ad-hoc basis as a reaction to events or problems.
• Poorly defined roles in terms of DA. Managers analyse and interpret data almost on goodwill.</td><td>• Flat structure, clearly defined business functions through cross-functional interaction is heavily encouraged.
• Management work with employees to provide quick feedback.
• Over interaction has slowed processes but improved effectiveness.</td><td>• Traditional, functional and bureaucratic.
• Decisions are generally top-down and bottom-up decisions are heavily scrutinised.
• DA in one function is not shared with other functions but IT sits in the middle of the organisation with a mandate to support all business needs.</td><td>• The functional organisation, but in terms of data, BI merges data from different functions adopting a process approach.
• President is the owner and has ultimate decision power. The culture of data analysts of the board is driving the DA future development.
• The roles in terms of DA are well defined</td><td>• Functional organisational structure.
• Although governed by family, the formalization of the managerial process is increasing with key functions being managed by people outside.
• The key role of the ICT function is to supply information to favour integration and support the activities from various functions.</td></tr>
<tr><td colspan="7">Quotations:
"The silo structure of the organisation has a clear impact on the flow of data across the different departments - C1
"Bureaucratic structure of the organisation is preventing access to understand business-level data and sales performance" - C2
"Top-level management are advocates of increased data usage for decision making and an active drive towards it is necessary for increased success" - C1
"We would not force employees to use unknown systems, so we engaged two control managers to support effective data capturing and analysis" - C7
"Workers are empowered more to explore themselves and feedback to us" - C4</td></tr>
</table>

Performance measurement system	• Balanced set of measures used at the strategic level with focus on customers • Measures are limited to their business functions (due to silo structures) • Some of the new trends and measures were explored from social media data, which is rather exploratory without strategic intent. • Measurement capabilities and best practices: real-time data, data accuracy, data validity, data-driven culture, analytical tools skill-set, quick access to information • Few predictive KPIs used: Customer conversion rate, User engagement and reach	• Balanced set of measures are used which are focussed on efficiencies with little focus on customers • Due to restricted access to data, the measures are only deployed to few decision-makers on request • Information flowed upwards, where senior management made decisions using KPIs. • Measurement capabilities and best practices: real-time data, data accuracy, data validity, data-driven culture • Few predictive KPIs used: Overall Equipment Effectiveness, Customer satisfaction	• Balanced set of measures largely driven by business customers. These measures are focused on operational efficiencies. • Only very few key decision-makers have access to measures. • Targets, which are driven by key customers, are the main focus of senior key decision-makers. • Measurement capabilities and best practices: none • Few predictive KPIs used: Demand forecasting, On time delivery, customer complaints	• Balanced set of measures used at the strategic level with focus on customers • Due to the flat structure, most of the managers made routine decisions based on KPIs • Information flowed upwards where senior management made strategic decisions on KPIs. • Measurement capabilities and best practices: real-time data, data accuracy, data validity, data-driven culture, analytical tools skill-set, quick access to information • Few predictive KPIs used: Lead conversion, Average cost per lead, Client satisfaction	• Balanced set of measures used at the strategic level with focus on customers • Due to the bureaucratic structure, measures are deployed to a few people on request • While they have sophisticated data capturing systems, the data is rather exploratory with no strategic intent. They are underutilising data. • Measurement capabilities and best practices: real-time data, data accuracy, analytical tools skill-set • Few predictive KPIs used: Metering efficiency, Customer life time value, Customer satisfaction	• Wide set of measures with particular attention to customer and sales management and poorly integrated. • Sales trends, and financial performance are available to all process owners by online tools • Targets are strongly linked to company strategy but not related to incentives. • Measurement capabilities and best practices: real-time data, data accuracy, data validity, data-driven culture, analytical tools skill-set, quick access to information • Few predictive KPIs used: Productivity, No of new sales practices share on line, No. of customer complains ,	• Although there is a balanced set of measures with high customer focus, they are not integrated at business level (limited to functions) • Data are mainly used to support operational decision • The entrepreneur often asks for ad hoc information to support strategic decision • Targets are often not fixed • Most of the measure are not linked to company strategy • Measurement capabilities and best practices: real-time data, data accuracy, data validity, data-driven culture, analytical tools skill-set, quick access to information • Few predictive KPIs used: New product development lead time, No: of new products launched, Production efficiency

Data capturing.

The seven case studies showed rather different attitudes towards data collection and recording. All cases (except C3) were sophisticated in terms of recording data. Most of the cases have developed different levels of infrastructure for data capturing systems ranging from manual entry to autonomous sensors for monitoring on-site activities to off-site activities. C1 has *automated* the majority of their data capturing systems, although they still have some technical difficulties. C1 and C4 organisations showed high levels of commitment to ensuring that good levels of accuracy and timeliness of data are respected as they can see the *value of data*. Both have some strategic intents for their data gathering and they capture both structured and unstructured data to fulfil their needs, although these can be improved further.

Although there is a commitment, all six cases have serious issues with data handling, mainly caused by shortcomings of the organisational "structure" capability, which will be discussed subsequently in this section. At C2, C5 and C7 there are accuracy issues making the management sceptical about the way data is being captured (likely manual entry) and hence the internal validation processes in place while making constant efforts to improve accuracy at the source. On the other end of the spectrum, C3 demonstrates an almost opposite style to the other cases in terms of their handling of data. Despite their daily requirements for accurate production planning data, which are normally pushed by their customers, C3 is clearly far behind in terms of capturing and storing data. Not only some of the basic operational data, such as stock levels, are not even captured. The transactional data are recorded 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 issue.

Some of the cases studied have seen the advantage of *data variety* and started collecting for enhanced decision-making. In addition to collecting numerical data in all cases studied, C1 has started collecting unstructured data from social networks in evaluating their expansion decisions. C2 has started collecting qualitative data to assess customer satisfaction. C4 was collecting data in a range of structures (i.e., non-numeric and video format) from numerous sources. C6 was collecting data from social media to evaluate its product performance. C7 was engaging academic and student communities to gather information on new trends and ideas for their creative furniture designs. In all these five cases, organisations are gathering new business insights for decision-making, which wouldn't have been possible without new data variety.

Data analytics (DA)

Data capturing is linked very closely to the analytic capability across the seven cases. The DA capability proved to have a direct impact on the organisation's ability to extract meaningful and useful intelligence required by PMS to support the decision-making. For instance, cases C1, C4 and C6 have relatively more sophisticated data capturing practices(i.e., higher degree of automation and fewer accuracy issues), 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. At C6, they recruited a new HR manager to develop necessary *analytical and interpretation skills* and promote the use of data to enable information-based decision-making in the organisation. Similarly, at C4 the management invested in both systems to enable DA (including the third party software) as well as in designing tailored *training* to develop *analytical skills*. However, it is found that while the data capturing systems are sophisticated at C5 along with enthusiastic staff with required analytical skills, their ability to perform DA is limited for two reasons. Firstly, there is poor integration between the data sets, which are segmented into different competitive business units along with the *lack of skills* to manage them. Secondly, there is a lack of senior management commitment holding their dearth for DA.

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 (C2, C5 and C7) 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. In the case of C2, there are concerns about the accuracy of some data, due to it being input manually, where substantial efforts go 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. While they have access to standard information created by shop floor data capturing systems, people often have to stick to what is available, restricting the full potential of information use. The situation at C7 is similar but, however, they started investing in appropriate infrastructure and engaging control managers to cross-functional boundaries and support employees in their *information-based decision-making*.

The case of C3 demonstrates even more severe issues due to the inadequacy of their data capturing practices. Their inability to integrate business processes due to their primitive systems often gives them very little information on what is happening with the business. Aspects of stock control, for instance, have had a significant negative impact on their ability to plan and produce accurately, often resulting in fines because of missed deadlines. The complexity of their customer demand makes it difficult for them to interpret things promptly and feed them into the production processes. This is more evident in their planning, where intuition is mostly the only best practice they go by. The company finds data retrieval so problematic that the bulk of its analytics is mainly based on the managers' intuition and experience, which seems to have been working adequately so far. However, C3's growth has increased so much that its 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.

In addition, at C1, senior management is interested in understanding customer/consumer habits and behaviour and is putting the right resources into capturing such information and developing the evidence-based decision-making culture. Whereas at C4 and C6 the senior management is providing necessary training to their employees in developing their *analytical skills* to create an *information-based decision-making culture*. Similarly, 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.

It is evident from the seven cases that DA converts data into more meaningful information (for instance, *visualisation* of data on shop floors, PCs, billboards, etc.) 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 empower them. Moreover, it is essential that employees are trained on DA to overcome their resistance and enable data-based decision-making.

Organizational structure capability

Except for C4, all the remaining six cases have silo-based (i.e. functional) and hierarchical structures. C4 has a flatter structure with fewer layers of management, enabling quicker *channels of communication* to support their employees. This, along with data analytics (DA), enabled employees to be more autonomous in making decisions. C6 has a silo-based structure with layers of management with a top-down approach. However, they have overcome their structure issues by employing an HR manager along with sophisticated DA to drive data-driven decision-making culture across the departments. The cases of C1 and C5, 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. In addition, the senior management at C5 adopted a top-down approach relying on their experience in contrast to relying on the information.

At C2 due to the silo structure, often the non-standard information requests always took a long time, making it difficult to support decision-making. In contrast, at C7 they are overcoming the silo structure by engaging control managers to work across the departments to communicate and share information to enable decision-making. Furthermore, the case of C3 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.

In fact, silo structure obstructs the *communication* processes and the development of PMS and the effective use of information for decision-making process. To overcome this, an integration mechanism is required to enable the flow of information between different levels and across the departments with clear *channels of communication*. At C1, C4 and C6 *senior manager drive* played a significant role in processing data to support decision-making. The information is communicated to the people who need it, which is creating transparency and empowering people at large. 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 the full potential of DA.

At C2 and C6, DA plays an important role at a senior level in supporting their decision-making. Standard information is available with the appropriate access to different employees, which created transparency in the organisations. They also developed decision support tools for improving their planning and forecasting decisions on a day-to-day 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 organisations from gaining full potential of it. While C5 enjoys some of the benefits highlighted above, the usefulness of DA is restricted due to the lack of senior management drive. This is resulting in the organisation taking a reactive approach to the needs in a situation. At C3, 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 the 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 more concerned with their day-to-day jobs, and therefore make decisions intuitively.

Discussion

In studying decision-making in data-intensive environments, a few important elements emerged from the literature and the empirical study. In particular, it is clear that a rational decision-making process is based on several phases (Baum and Wally, 2003, p.1109) and relevant resources and capabilities are crucial for its effectiveness. This is particularly valid in the current business climate, which is characterised by a rapid and almost uncontrollable increase in the amount of data flowing through organisations.

The first capability that emerged here is that of *data capturing (DC)*, which looks into how organisations capture their data and the reasons behind it. According to Baum and Wally (2003, p. 1109), it is necessary for organisations to explore and analyse the options they need to develop and evaluate. From a capabilities perspective, what should be noticed here is that none of the studied cases presents data capturing as a strategic capability. All the cases showed rather standard levels of data capturing that were not rare enough to have a serious strategic impact. However, there were some clearly differentiating resources under the data capturing capability. Automation is one of those resources that has emerged as an enabler for a superior data capturing capability, although it is not particularly rare. The seven cases have demonstrated that automation is essential to improve accuracy and enable effective decision-making. There is a diffuse use of spatially distributed autonomous sensors with a communications infrastructure for remote environmental and physical monitoring, capable of collecting, storing, and processing large amounts of data (Janssen et al., 2017; Ford 2009; Hershey 2018).

Proposition 1: A higher degree of automation is required to ensure timely and accurate decisions to drive superior performance.

A second important resource that emerged rather strongly is the level of awareness of the value of data, even though the literature pays little attention to awareness (Sargut, 2019; Tuptuk and Hailes 2018). In this study, it particularly emerged as a major enabler for developing the data capturing capability. With the increasing awareness of the value of data, people begin to improve the quality of data captured and how to use these data better.

Proposition 2: A higher degree of awareness of data value increases the effort in capturing accurate and timely data in effective decision-making.

From the analysis of the seven case studies, it is clear that 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 such data (LaValle et al., 2011; Davenport et al., 2012; Constantiou and Kallinikos, 2015). As Davenport et al. (2012) explained, companies wishing to take advantage of data need to learn how to collect data in real-time and through a variety of means such as sensors, radio frequency identification, and other non-numerical data.

Proposition 3: Data variety increases the scope of business insights for effective decision-making.

The second capability that emerged is ***data analytics (DA)*** which looks into how the collected data is processed into information suitable for decision-making, be it for developing new opportunities, testing and improving existing opportunities, or simply for problem-solving. From a capabilities perspective, the two main factors that would influence DA capability are developing the right analytical skills as well as interpretation skills for generating business insights, which would lead to more effective decision-making (Ghasemaghaei et al., 2018; Akhtar et al., 2018, 2019; Davenport and Patil, 2012). When analysts have no appropriate analytical skills, they tend to either postpone their tasks, or take longer and potentially make mistakes, which will lead to suboptimal decision-making (Ghasemaghaei et al., 2017). While the analytical skills are at varying levels in all seven organisations (through either their own departments or through IT department), none of them is developing it as a strategic capability thus resulting in suboptimal decision-making. Hence, drawing on Bharadwaj's (2000) IT-based resources framework, analytical skills and human IT resource are considered the critical dimensions of data analytics capability.

Proposition 4: Data analytical skills are required to derive business insights for effective decision-making.

In addition, a wide range of visualization tools is becoming increasingly relevant (from common bar graphs to sophisticated virtual environments). Visualization tools emphasize context by showing the relationships between different pieces of information and shifting cognitive load to the human perceptual system through graphics and animations (Lohse, 1997 Davison, 2015; Quattrone 2017). In six organisations, visualization tools are being deployed at varying degrees, but much of it is static, requiring some form of human intervention (communication), thus delaying decision-making in real-time. Hence, as Kim et al. (2012) highlighted, visual representations strengthen problem-solving capabilities by enabling the processing of more data without overloading the decision-maker.

Proposition 5: Data visualisation and communication are required to derive better inferences for effective decision-making.

Effective data capturing, analysis and use requires a data-driven culture to create effective information, an atmosphere of trust and data-informed inquiry (Silvola et al 2011; Brynjolfsson et al 2011). Kamble and Gunasekaran (2020) argue that data-driven culture is an outcome over a period of time, where the management emphasises the importance of valid data, analytical skill-set for processing it, and transparent communication to relevant people for effective decision making.

Davenport and Patil (2012) identified that the dearth of data scientists is a serious concern in several organisations impeding the data-driven culture. At least in four cases, senior management are emphasizing the access to and use of information in decision-making. In two of these cases, they even employed managers to promote the collection of data, its analysis, communication and use. Hence, a data-driven culture that could amplify greater efficiency in the use of data is identified as a key dimension.

Proposition 6: Data-driven culture needs to be developed to collect, process, communicate and access information for effective decision-making.

As the literature suggests (Bower, 1970; Csaszar, 2012), in the investigated case studies, 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. From a capability perspective, senior management commitment emerges as crucial and takes the initiative in driving the culture of employees making autonomous decisions based on the evidence, thus cultivating data-driven culture. It is evident from the seven cases that DA demonstrated significant impact on understanding customer behaviour, enabled targeted sales promotion, increased sales and profitability. Moreover, senior management involvement demonstrated a significant impact on lower-level management decision-making, thus improving optimised resource utilisation, efficiency and effectiveness, increased production as well as optimized inventory. In contrast, it is also evident that the 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, capabilities and processes. Bititci et al (2006) argued that support from senior management in the form of drive and commitment is imperative. Moreover, as the MIS literature highlights, senior managers play a significant role in making people analyse data (Bourne et al., 2000). Hence it is evident from the literature that senior management commitment should come in the form of drive to manage the change and influence behaviours in these organisations (Bititci et al., 2006; Franco-Santos et al., 2007). As highlighted by El-Kassar and Singh (2018), the assimilation of big data is strictly related to senior management commitment that should mitigate and overcome the resistance from people. As Smith and Bititci (2017) identified, senior management commitment and drive are essential in making organisations use performance measurement to empower people as well as enhance their improvement culture, which will eventually promote proactive decision-making.

Proposition 7: Senior management should drive to create appropriate resources and capabilities to cultivate a data-driven culture for effective decision-making.

However, from the seven cases, it is argued that support should come through organisational structure, i.e. by creating clear channels of communication of data and information at various levels, across the business functions would enable timely and informative decision-making. In the investigated companies, structural elements have often had the unintended consequence of inhibiting collaboration and sharing of data across internal organizational boundaries. Structures promoting individualistic behaviour have inhibited effective data collection and analytics across the organization. The optimization of data collection and analytics within a functional area sub-optimize the sharing of knowledge across the organization. In essence organizational structure should be designed for encouraging sharing and collaboration across boundaries within the organization and across the functional areas.

Proposition 8: Appropriate organisation structure should be developed to create clear channels of communication at various levels for promoting effective decision-making

From a capabilities perspective, and very similar to the other dimensions discussed above, organisational structure seems to be a major enabling resource but did not show any extreme level of strategic relevance. What became strongly evident from the cases is that the combinative power of "data capturing" and "data analytics" will be influenced by "organisational structure".

The seven cases demonstrate, rather firmly, that organisational structure directly impacts the effectiveness of "data capturing" and "data analytics", and their integration, consequently has a direct impact on the effectiveness of decision-making processes. The organisational structure has a detrimental impact on the organisations' ability to capture data and produce sophisticated analytics. Due to the silo structure, KPIs differed from one 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.

Proposition 9 - Organisational structure will significantly influence the combinative power of "data capturing" and "data analytics".

In each of the seven organisations, although not effective, decision-making processes are influenced by data capturing and analytical resources and capabilities that are limited by their PMS and KPIs. Such measurement systems determine the data that needs collecting for a purpose, which is also echoed by Bititci et al. (2012) and Nudurupati et al. (2021). They also provide information useful to formulate strategies and feed competitive advantage (Ittner et al., 2003). PMS is useful in translating strategy into action, leveraging on the communication of what measures need to be analysed and presented to people to enable decision-making (Bourne et al., 2000). It can be argued from the cases that if PMS with a strategic intent is well integrated with data collection and analytics capabilities, and supplemented by supportive organisational structure, it could enhance decision-making as a core capability to create competitive advantage.

Proposition 10 – Performance measurement system should have a strategic intent for developing data capturing and data analytics capabilities for effective decision-making.

From a capabilities perspective, and similarly to the previous dimension (data capturing), six of the cases presented basic analytic capabilities of processing data to measure performance in making routine decisions. There were clear differences (substantial in some cases) between the different studied organisations in terms of the level of sophistication of their data analytics capability. However, none of them exhibited significant levels of strategic relevance associated with data analytics capability. Nevertheless, it has become evident from these cases that there is a level of complementarity between the "data capturing" and "data analytics" capability. Although none of these capabilities emerged as strongly strategic in their own right, their integration showed clearly some strategic strength. For instance, if an organisation has data capturing as a significant capability while its analytical capability is not significant, it can still potentially create and sustain a competitive advantage. Hence, complementarity plays a significant role in creating competitive advantage. The combinative power of the two capabilities (although not strategic independently) enabled the organisations that have them to perform noticeably better compared to the rest (see for instance C1 and C4).

Proposition 11 – Performance measurement system should develop complementarity between data capturing and analytical capabilities for creating a competitive advantage

Conclusion

While the literature supports the argument that PMS supports decision-making, it is less clear on the nature of this relationship, i.e., which aspects of PMS will support what aspects of decision-making (LeRoux and Wright, 2010). This paper has presented a topical area of research and contributed to positioning PMS in data-intensive organisations where data capturing and analytics are paramount. With the evolution of information technologies, 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.

The study is novel in the sense that it is claiming that organisations need to establish a PMS to scale down huge amounts of data to key information to enable effective decision-making. It has also contributed by identifying data capturing and analytical resources and capabilities to flourish in such environments to create competitive advantage. After looking into seven quite distinct case studies, this paper puts forward eleven propositions, synthesized in Table 3 and Figure 2.

Table 3: Emerging Propositions

Capabilities		Emerging propositions
Data capturing capability	*P1*	*– A higher degree of automation is required to ensure timely and accurate decisions to drive superior performance.*
	P2	*– A higher degree of awareness of data value increases the effort in capturing accurate and timely data in effective decision-making.*
	P3	*– Data variety increases the scope of business insights for effective decision-making.*
Data analytics capability	*P4*	*– Data analytical skills are required to derive business insights for effective decision-making*
	P5	*– Data visualisation is required to derive better inferences for effective decision-making.*
	P6	*– Data-driven culture needs to be developed to collect, process, communicate and access information for effective decision-making*
Structure capability	*P7*	*– Senior management should drive to create appropriate resources and capabilities to cultivate a data-driven culture for effective decision-making*
	P8	*– Appropriate organisation structure should be developed to create clear channels of communication at various levels for promoting effective decision-making.*
	P9	*– Organisational structure will significantly influence the combinative power of "data capturing" and "data analytics".*
Performance measurement systems	*P10*	*– Performance measurement system should have a strategic intent for developing data capturing and data analytics capabilities for effective decision-making*
	P11	*– Performance measurement system should develop complementarity between data capturing and analytical capabilities for creating a competitive advantage*

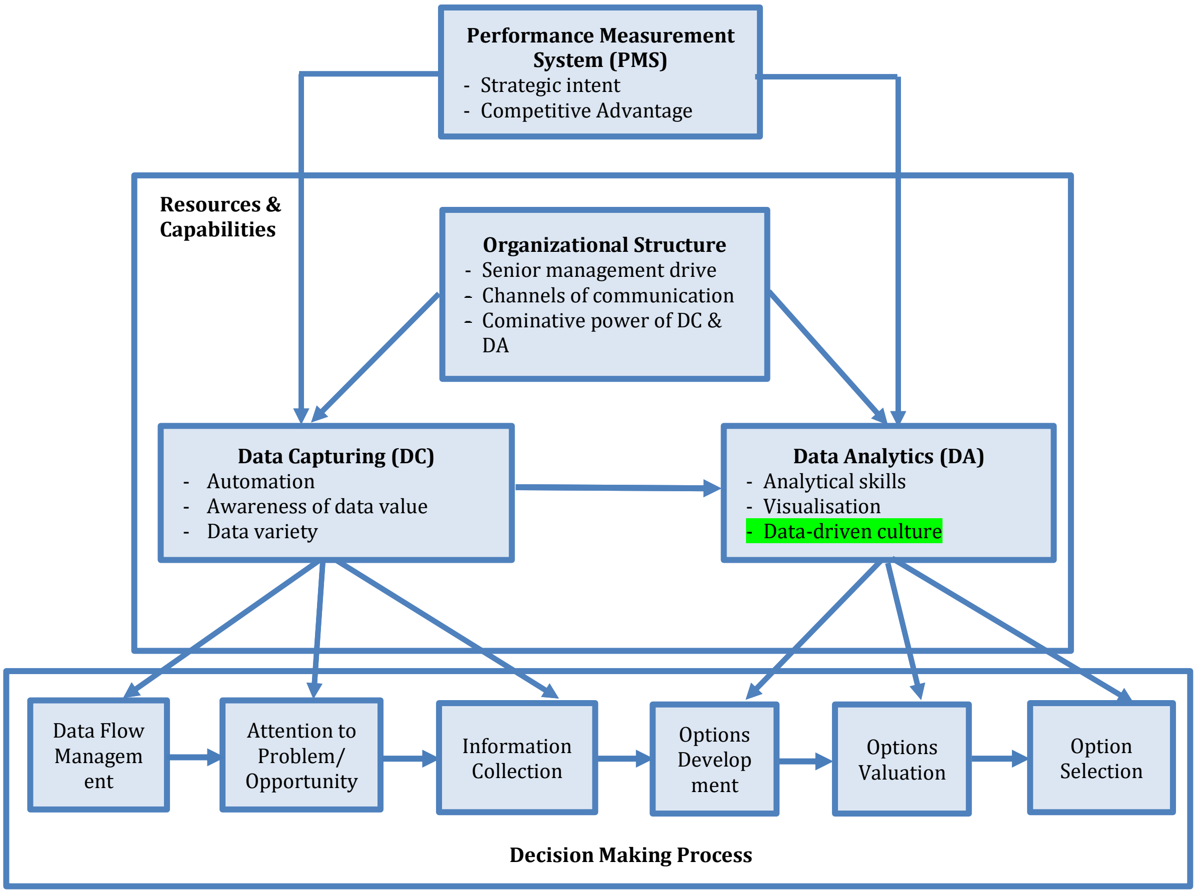

Figure 2 Influence of PMS on resources and capabilities to support the decision-making process

Theoretical implications

As demonstrated in Figure 2, an important outcome of this research is that *"organisational structure"* has clearly emerged as a resource of major strategic importance for realising the benefits of data analytics. All the case studies displayed shortcomings in their structure that impede the effectiveness of their data analytics practices and the resulting decision-making processes. Not only does organisational structure play a vital role in enabling data capturing and analytics practices, but also the role of senior management in driving these practices and empowering data scientists is of prime importance. The organisations structure would enable open channels of communication at different levels across various departments for free flow of information for effective decisions. Moreover, the use of the capabilities perspective has demonstrated that the combinative power of specific resources and capabilities can yield superior results, or at least give organisations enough distinctiveness to be able to conceive unique advantage that may improve their strategic position. The study has identified that a higher degree of automation, a higher degree of awareness of data value, and data variety are important aspects in strengthening the data capturing capability. Similarly, data analytics skills, data visualisation and data-driven culture are important aspects in strengthening the data analytics capability.

In this paper, although *"data capturing"*, *"data analytics"*, and *"organisational structure"* did not present strong strategic characteristics individually, their combination in some cases proved to be a major enabler for distinctive results. In particular, the *"data capturing"* capability seems to directly impact the *"data analytics"* capability. those organisations that lacked a well-developed data capturing capability had severe difficulties developing a mature data analytics capability. Moreover, *"organisational structure"* proved to be a resource of utmost importance in that it acts as an enabler of *"data capturing"* and *"data analytics"*. It was evident from the cases that all the cases with poor organisational structure (bureaucratic, top-down and inefficient) have severe difficulties developing and organising their data capturing and analytics capabilities. Ultimately, organisations that have an efficient structure, and have strong data capturing and data analytics capabilities, have the potential to enjoy superior performance compared to those that do not have access to such resources and capabilities or have an incomplete set.

Managerial implications

As demonstrated in Figure 2, it is clear that organisations can find themselves at varying stages in their awareness of the value of data and the exploitation of data analytics in their daily and strategic activities. The cases in the study demonstrated, very strongly, the impact of such varying stages on decision-making. In essence, such performance is driven not only by the organisation's strategic intent to capture and analyse the key data but also by the opportunities emerging for the continuous flow of data to different levels across various departments. This 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 study has also demonstrated that organisations that failed to establish such a relationship result in a rather chaotic situation, very reactive and lacking in strategic direction. Moreover, it re-echoed Davenport and Patil's (2012) arguments that nurturing data scientists will increasingly become fundamental to organisations' success in a contemporary business environment often characterised as fast-paced and data-intensive. However, the paper argues that having desirable data scientists is only part of the requirements as these need to find themselves in optimal working conditions to be able to contribute effectively.

Limitations and future work

This study has some limitations, without which the results could have been even better. Data were collected from seven cases, which have informed this research rather strongly. This is a limitation of qualitative research in general, as the breadth will seldom be sufficient to draw industry/sector-wise implications. However, a much larger data set in the form of quantitative data from various sectors would have been ideal for strengthening the identified patterns and drawing out wider generalisability. Nevertheless, this exploratory study with the eleven propositions would be a starting point for conducting large-scale studies. Moreover, although decision-making is of core focus, this research has not explored the element of the 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 looking into the impact of data analytics on decision-making and exploring the link between the dimensions discussed above and the success of decision-making (managerial or strategic).

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Appendix A Data collection and analysis protocol

	Description
Unit of analysis	Seven data-intensive organisations ranging from manufacturing, retail and service sector
Data collected by	Two researchers following a standard interview protocol to reduce variation
Data source	• Interviews: one to one interviews with management team members • Observations: Personal observations of the researchers who have access to the organisation over the years • Documents: Company documentation such as business reports, performance reports, meetings notes, etc.
Data collection structure	Data collection protocol included the parts listed below **PART I: ORGANISATION'S BACKGROUND** • Organisation's history: the company profile, historical background, organisation chart and information on the existing information system and the performance management system. • Governance structure: family firm; managerial structure, ownership and decision power • Organisation's business strategy: mission statement, business strategy and key assets and resources • Business operation configuration: identification of key processes and products/services; customers/markets, channels, etc. **PART II: MAIN ISSUES RELATED TO ORGANIZATIONAL STRUCTURE, DATA CAPTURING, DATA ANALYTICS, DECISION-MAKING PROCESS AND PERFORMANCE MEASUREMENT** • What is the current structure of the organisation? Where does IT sit in this structure • How are decisions made in the organisation? (i.e. bureaucratic, autonomous, etc.) • How is data gathered in the organisation? • What happens to data next? • How is data analysed? Who does what? Any examples or demonstration will be useful • Are people competent in doing their own analysis or is it done centrally and communicated? • How is it communicated across the business? To the decision-makers? • Are decisions based on information? If not, why not? • Is there a strategic intent for data analytics? • Is the information available on a timely basis to enable fast decision-making? • Can you provide examples on the type of decisions made based on information • Are these decisions improving performance? Can you give examples of improvement? • What impact does analytics have on your organisation? • Do you think the existing organisational structure is enabling timely information-based decision making? If not, why not? How can this be improved? How do you think should the organisation structure need to change? • What type of measures do you use in the organisation? • How are measures deployed to lower levels? • Is there a strategic intent for developing data capturing or analytical resources and capabilities
Data validation	• Interviews were recorded and used to create interview reports that included interviewers' interpretation of the interview • The interview reports were discussed between the three researchers involved in data collection • Interview reports were sent to the interviewee for verification of accuracy and the interviewer's interpretation • Feedback was used to make any amendments to interview reports
Analysis	**WITHIN CASE ANALYSIS** Using the collected data, a report was produced using the following structure: • **Background of company**: the historical background of the company, its location and number of employees. • **Company products/services**: the company's main services or products. • **Data summary**: the raw data obtained from the company based on the questions asked • **Data analysis:** researcher followed the suggestions made by Miles and Huberman (1994). Three concurrent activities were followed: data reduction, data display, identifying common themes and trends, finally drawing conclusions or verification. **CROSS-CASE ANALYSIS** Using empirical data across all four cases, the following techniques were employed in synthesizing the findings: • Observations of data • Manual coding and content analysis • Manual pattern analysis for developing integrative explanations