Using Business Analytics to Enhance Dynamic Capabilities in Operations Research: A Case Analysis and Research Agenda

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Abstract: *While the topic of analytics is rapidly growing in popularity across various domains, there is still a relatively low amount of empirical work in the field of operations research. While studies of various technical and business aspects of analytics are emerging in OR, little has been done to address how the OR community can leverage business analytics in dynamic and uncertain environments – the very place where OR is supposed to play a key role. To address this gap, this study draws on the dynamic capabilities view of the firm and builds on eight selected case studies of operations research activity in large organisations, each of whom have invested significantly in analytics technology and implementation. The study identifies fourteen analytics-enabled micro-foundations of dynamic capabilities, essentially highlighting how organisations can use analytics to manage and enhance their OR activities in dynamic and uncertain environments. This study also identifies six key cross-cutting propositions emerging from the data and develops a roadmap for future OR researchers to address these issues and improve the use and value of analytics as enablers of organisational dynamic capabilities.*

Keywords: *analytics, dynamic capabilities, agility, operations research*

1. Introduction

The popularity of analytics increased tremendously in the last decade, 'rocketing' to the top of the corporate agenda, with claims that *"data is the new oil"* to be *"refined"* to extract unprecedented value (Brown et al., 2011). In the business world, the data deluge has sparked the interest of almost every industry to develop capabilities to extract insightful knowledge from data and achieve a competitive advantage (Provost & Fawcett, 2013). Nevertheless, these new data sources are often too large, too complex, and are generated and become obsolete at such a speed that renders traditional analytics methods as ineffective in extracting any meaningful insight (Delen & Zolbanin, 2018). In response to these issues, novel methodologies and processing techniques have given rise to a new era in business decision making, referred to as the business analytics period (Mortenson, 2015). Business analytics is concerned with the context in which these techniques are applied on big data[1] to make sounder, more evidence-based business decisions (Seddon, Constantinidis, & Dod, 2012). As a result, business analytics can enable descriptive, predictive, and prescriptive model building using diverse, real-time, and "big" data sources (Duan, Cao, & Edwards, 2018; Hindle & Vidgen, 2018). Many in the operations research (OR[2]) community have cited the prominence of business analytics as an opportunity that could "promote the [. . .] profession and expand its reach" (Liberatore & Luo, 2010) and improve the

[1] In this study we base our definition of big data on having three main characteristics. These include 1) volume - referring to the large amount of data, 2) velocity – referring to the speed that data is generated and processed, and 3) variety - referring to the multitude of sources and formats that the data include. Nevertheless, we also acknowledge that this data can be described by additional characteristics in accordance with relevant recent literature.

[2] While there are numerous definitions of OR we, like many, adopt the Operational Research Society's (2016) definition as "the discipline of applying advanced analytical methods to help make better decisions". Specifically, however, we were guided by previous seminal studies such as the ten most prevalent OR techniques identified by Ranyard et al (2015), O'Brien et al (2011) and others. These are: *spreadsheets (basic and advanced), statistics (basic and advanced), optimisation, strategic planning tools, simulation, forecasting, scheduling* and *decision support systems.*

prevalence and effectiveness of OR activity in enhancing business value (Mortenson, Doherty, & Robinson, 2015; Vidgen, Shaw, & Grant, 2017).

While there is a growing body of literature, on the value of business analytics in other domains such as information systems research (Abbasi, Sarker, & Chiang, 2016; Côrte-Real, Oliveira, & Ruivo, 2017; Seddon & Currie, 2017; Shanks, Bekmamedov, & Sharma, 2011; Shanks & Sharma, 2011; Torres, Sidorova, & Jones, 2018); in the OR discipline is surprisingly, and problematically low (Grover, Chiang, Liang, & Zhang, 2018; Mikalef, Boura, Lekakos, & Krogstie, 2019b; Mortenson et al., 2015; Ranyard, Fildes, & Hu, 2015; Vidgen et al., 2017). Ranyard et al. (2015) refer to business analytics as a means to extend the scope of OR practice, but the exact relationship between business analytics and OR remains a topic of much debate (Duan et al., 2018; Royston, 2013). The body of work in this stream of business analytics research has also been criticised for an absence of theoretical grounding, for lacking clarity of definition and scope, and represents "a noticeable resistance from the traditional OR community to the need to respond to the distinctive features of analytics" (Ranyard et al., 2015). Recent research has now started to address this gap, highlighting key OR challenges in eliciting value from business analytics (Vidgen et al., 2017), or providing frameworks for the deployment of OR analytics (Hindle & Vidgen, 2018).

While it is encouraging to see this emerging stream of research, the extant literature to date has not specifically examined how organisations leverage these technologies under conditions of turbulence and uncertainty to address emerging opportunities and threats (Mikalef, Pappas, Krogstie, & Giannakos, 2017). This is surprising for several reasons:

(i) OR activities often become more valuable or indeed critical in highly uncertain, turbulent and dynamic environments (Constantiou & Kallinikos, 2015). There is a rarely questioned assumption that our 'now' is more ephemeral, evanescent than ever before, and that any organisation's use of technology must help them survive and thrive in the seemingly never-ending change (Kavanagh, Lightfoot, & Lilley, 2007).

(ii) Information is not static; hence, there is no option but for business analytics to handle 'data in motion', as the desired patterns and insights are a moving target (Abbasi et al., 2016).

(iii) OR activities and analytics data typically have a time value (Grover et al., 2018), and therefore, the speed with which OR activities can draw on business analytics to add value affects the value of that activity. For example, an analysis report five minutes before a meeting or before a share price announcement may be incredibly valuable; one second after that meeting or announcement, the value may drop to zero.

(iv) Even in the unlikely event that the value of analytics data remains constant, the fundamental nature of that data changes over time. Such issues include the growing diversity of such data, the frequency by which it is updated, and the speed by which it grows (Davenport, 2014). As a result, failure of OR activities to incorporate such changes in nature reduce the value of the analytics function (Constantiou & Kallinikos, 2015).

Given these reasons, managing this dynamic, changing nature of data necessitates that firms form an analytics-specific governance plan to elicit and maximise value that can be derived through business analytics. Notably, Mortenson et al. (2015) highlight the need for OR research to address the areas outlined above and bring it to the attention of the wider OR community, through case studies and/or literature reviews.

We address this call by adopting a dynamic capabilities perspective (Schilke, 2014a; Teece, 2007) to examine the use of business analytics in eight 'revelatory' case studies of analytics-enabled OR activities. Dynamic capabilities can be disaggregated into three distinct activities: *sensing* opportunities and threats, *seizing* those opportunities, and maintaining competitiveness by *transforming* resources and capabilities (Teece, 2007). Therefore, the questions addressed in this study are:

1. How does business analytics facilitate value through OR-enabled dynamic capabilities i.e. *sensing*, *seizing* and *transforming*?
2. What over-arching factors may affect how analytics in OR can enable dynamic capabilities?

The next sections of the paper summarise the pertinent literature and describe the theoretical basis and research approach adopted in this study. In section 3, the cases are presented and discussed, and through further analysis in section 4, several key cross-cutting propositions are developed, along with a roadmap for future research. The paper concludes with the implications of this study for OR researchers, practitioners and educators.

2. Theoretical Background

2.1 Dynamic Capabilities

The Dynamic Capabilities View (DCV) has emerged as one of the most influential theoretical perspectives in the study of strategic management over the past decade (Schilke, 2014a). Grounded on the Schumpeterian logic of creative destruction, dynamic capabilities enable firms to sense and seize emerging business opportunities, and to transform their operations in order to adapt to changing market conditions (Teece, 2007). Despite considerable variation in definitions, there is increasing convergence on the idea that dynamic capabilities are purposefully developed and are comprised of a set of identifiable and specific routines (Eisenhardt & Martin, 2000). These routines are commonly understood as learned, highly patterned, and repetitious, directed towards independent corporate actions (Winter, 2003). A key reason for much research attention on the notion of dynamic capabilities has been their proposed influence on important outcome variables (Schilke, Hu, & Helfat, 2018). Dynamic capabilities effectuate systematic change, by enabling renewal of operational capabilities and increased flexibility in response to market changes (Pezeshkan, Fainshmidt, Nair, Frazier, & Markowski, 2016). These represent key areas in the attainment of a sustained competitive advantage (Teece, 2007).

Dynamic capabilities have been disaggregated into three types of activities oriented toward strategic change, namely *sensing* new opportunities and threats, *seizing* new opportunities through business model design and strategic investments, and *transforming* or reconfiguring existing business models and strategies (Helfat & Raubitschek, 2018; Teece, 2007). Teece (2007) notes that sensing involves analytical systems of scanning, search and exploration activities across markets and technologies. *Seizing* on the other hand entails evaluation of existing and emerging capabilities, and possible investments in relevant designs and technologies that are most likely to achieve marketplace acceptance (Wilden, Gudergan, Nielsen, & Lings, 2013). Finally, *transforming* includes continuous alignment and realignment of specific tangible and intangible assets (Katkalo, Pitelis, & Teece, 2010). While prior empirical research has predominantly examined the outcomes of dynamic capabilities (Drnevich & Kriauciunas, 2011; Protogerou, Caloghirou, & Lioukas, 2011) there have been several studies looking into the enablers of their formation (Capron & Mitchell, 2009). Such investigations have looked at antecedents at different levels of analysis, including the organisational (Eisenhardt, Furr, & Bingham, 2010), individual (Hsu & Sabherwal, 2012), and environmental levels (Killen, Jugdev, Drouin, & Petit, 2012), to isolate factors that either enable or hinder the formation of dynamic capabilities. Nevertheless, there is, to the best of our knowledge, no research that examines the impact of business analytics on the creation of dynamic capabilities, and particularly on each of the underlying types of activities that comprise them (see Table 1).

	Sensing	**Seizing**	**Transforming**	**Reference**
Definition	the identification and assessment of opportunities	the mobilisation of resources to address that opportunity	the continued renewal of the organisation	(Teece, 2007)
Underlying processes	• Gathering market intelligence • Spotting opportunities • Identifying target market segments • Spotting changing customer needs and customer innovation • Interpreting changes and uncertainties • New business models	• Building competencies • Choosing decision-making practices • Selecting partners and distribution channels • Committing to R&D • Mobilising resources to address opportunities • Forming alliances and joint ventures	• Achieving recombination's • Re-engineering processes • Reconfiguring capabilities • Managing knowledge • Asset co-specialisation • Dynamic alignment of assets	(Jantunen, Tarkiainen, Chari, & Oghazi, 2018; Katkalo et al., 2010; Teece, 2007; Wilden et al., 2013)
Value creation	• Positioning for first mover advantage • Determining entry timing	• Leveraging complementary assets	• Managing threats • Changing the business model • Continued renewal	(Katkalo et al., 2010; Teece, 2007)

Table 1: Dynamic Capabilities

While there is broad discussion on how business analytics can help organisations reposition themselves, there is a lack of understanding on how the characteristics that describe the data that is analysed and leveraged may affect each of the constituent dimensions.

2.2 Business Analytics

Business analytics are frequently referred to as the techniques, technologies, systems, practices, methodologies, and applications that enable organisations to analyse critical business data (Chen, Chiang, & Storey, 2012). Seddon and Currie (2017) propose a definition that is concerned with evidence-based problem recogniton and solving that occur witihn the context of business environments, namely *"the use of data to make sounder, more evidence-based business decisions"*. This is the definition adopted in this study. However, the extant conceptualisation and classification of business analytics is quite limited and what does exist (Holsapple, Lee-Post, & Pakath, 2014; Mikalef et al., 2017; Seddon & Currie, 2017) tends to vary greatly. In terms of getting to a more specific and operationalised definition of business analytics that can be used, this study draws on Mikalef et al. (2017), which systematically reviewed and consolidated the extant conceptualisations of business analytics. Their literature review showed that in terms of describing the data characteristics that underpin the notion of business analytics, many exist; however, the three key attributed include the *volume*, *velocity* and *variety* of data (McAfee, Brynjolfsson, & Davenport, 2012; Sun, Chen, & Yu, 2015). Several studies have adopted an extended view of data characteristics, including aspects such as *veracity* (Abbasi et al., 2016; Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016), *variability* (Hazen, Skipper, Boone, & Hill, 2018; Seddon et al., 2012) and *visualisation* (Seddon & Currie, 2017).

Given that this is an exploratory study, and one of the first in OR to explore how business analytics can underpin the processes that jointly comprise a firms overall dynamic capabilities, we chose to adopt a broader perspective regarding the data attributes that are relevant in business analytics. Consequently, we follow an inclusive approach drawing on the six aforementioned attributes (see Table 2). However, given that *volume, velocity and variety* are core attributes across all business analytics frameworks, our rationale is that these three attributes of data must be present in order to be classified as a business analytics case (Delen & Zolbanin, 2018; Vidgen et al., 2017).

Attribute	Definition
Volume *(Required)*	Volume represents the size of the dataset due to the aggregation of a large number of variables and an even larger set of observations for each variable (George, Osinga, Lavie, & Scott, 2016).
Velocity *(Required)*	Velocity reflects the speed at which data are collected and analysed, whether in real time or near real time from sensors, sales transactions, and sentiment data (George et al., 2016).
Variety *(Required)*	Variety in big data comes from the plurality of structured and unstructured data sources such as text, videos, networks, and graphics among others (George et al., 2016)
Veracity	Veracity ensures that data is trusted, authentic, and protected from unauthorised access and modification (Demchenko, Grosso, De Laat, & Membrey, 2013).
Visualisation	Visualisation ensures that the data is presented to the right audience in the right way at the right time (Seddon & Currie, 2017).
Variability	Variability concerns how insight from media constantly changes as the same information is interpreted in a different way, or new feeds from other sources help to shape a different outcome (Seddon & Currie, 2017).

Table 2: Data characteristics of business analytics

Based on these concepts, the role of business analytics in dynamic capabilities is discussed next.

2.3 Business Analytics as an Enabler of Dynamic Capabilities

To identify the challenges of an analytics-driven organisation, the framework introduced by Vidgen et al. (2017) built on the diamond model of the organisation of Leavitt (1965), a model which has “a long and distinguished provenance in socio-technical systems”. In the present study we build on the Vidgen et al. (2017) adapted framework in the following ways (Fig. 1). First, we inserted the dynamic capabilities listed in Table 1, namely *sensing, seizing* and *transforming*. Second, we use Leavitt’s (1965) four dimensions (*technology, structure, process, and people*) to illustrate the mechanisms and resources by which an organisation can achieve these capabilities. Third, we list the six Vs of business analytics data attributes from Table 2 that collectively and individually operate to enable these the three capabilities. As a simple illustrative example, to *sense* immediate problems or sales opportunities, sales representatives (*people)* on location can conduct sentiment analysis (*technology*) of all customers’ twitter activity from high *volume* and high *velocity* (real-time) data.data.

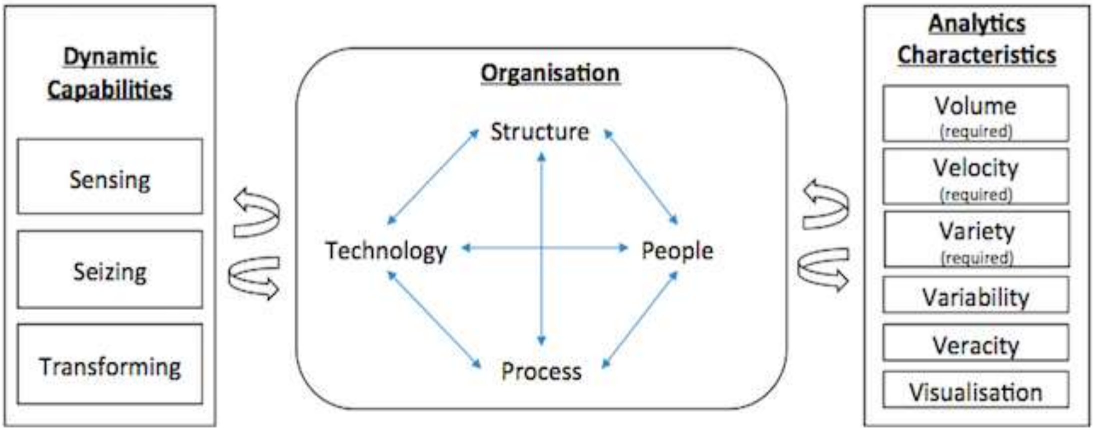

Fig. 1. Research Framework (adapted from Vidgen, Shaw, & Grant, 2017; Leavitt, 1965)

We view the four dimensions as the centre of the framework as it is these that enact the Vs. For example, having a high volume of data is mute unless it is leveraged through the people or processes that are sensing or seizing opportunities, for example. To date, a number of studies, while not empirically exploring these specific relationships, suggest that business analytics may have positive effects on a firm's dynamic capability processes (Côrte-Real et al., 2017; Gupta & George, 2016; Wamba et al., 2017). Erevelles, Fukawa, and Swayne (2016) put forth a conceptual framework which suggests that business analytics can enable the generation and use of consumer insights to enhance dynamic capabilities of sensing and transforming. A particularly critical enabler of processes underpinning dynamic capabilities is argued to be the data itself (Conboy, Dennehy, & O'Connor, 2018; Vidgen et al., 2017).

Vidgen et al. (2017) find through a Delphi study that in realising business value the veracity of data is the number one concern for managers, followed by availability and access to data sources, and security and privacy. Follow on cases, showed that data veracity was a primary concern amongst managers. This finding denotes that the characteristics of the data, significantly influences reaction time, a key component of a firm's dynamic capabilities. In a recent study, Côrte-Real, Ruivo, and Oliveira (2019) show that attributes of the data along with the organisational structure built around leveraging such data has a direct influence on the formation of dynamic capabilities. Nevertheless, there are still some major gaps regarding the effect that business analytics and the supporting data may have on enabling a firm's dynamic capabilities (Mikalef, Boura, Lekakos, & Krogstie, 2019a).

This study addresses some of these key gaps. First, while there is a nascent stream of research examining the role of business analytics within OR activities, there are strikingly few papers examining the business value of business analytics in such activities (Hindle & Vidgen, 2018; Vidgen et al., 2017). The few papers dealing with this topic either outline core aspects that require consideration by managers when delving into business analytics for OR activities (Duan et al., 2018; Vidgen et al., 2017), or describe the frameworks for guiding practitioners with activities pertinent to analytics deployments (Hindle &

Vidgen, 2018). Despite the value of these studies, it is critical to explore the multitude of ways through which business analytics can support dynamic capabilities in OR activities and ultimately lead to business value. Second, despite many calls in OR analytics research, there has been a lack of theoretical grounding of studies compared to other fields such as IS, and in particular in examining practice through the prism of theory (Ranyard et al., 2015). This lack of theory-based research has been explicitly pronounced in the area of business value of business analytics-driven OR activities (Duan et al., 2018). Third, while research in other domains has started to examine the impact of analytics on business value adopting a dynamic capabilities perspective, such effects are either examined and described at a higher, aggregate level (Wamba et al., 2017) or for isolated dimensions (Torres et al., 2018). In addition, the vast majority of such studies assumes causality of analytics through quantitative associations, therefore not exploring how business analytics feed into the underlying processes that comprise a firm's dynamic capabilities (Côrte-Real et al., 2017; Mikalef, Krogstie, Pappas, & Pavlou, 2019c).

The present study aims to extend current knowledge by unearthing the micro-foundations of sensing, seizing and transforming, and delineating the complex role of business analytics in enabling dynamic capabilities in OR activities. Fourth, the predominant view in examining business value of analytics has been based on a perspective of limited heterogeneity in capturing such effects (Gupta & George, 2016). The vast majority of research has assumed that effects of business analytics on underlying dimensions of dynamic capabilities do not vary greatly, and that a largely uniform set of aspects contributes to business value (Günther, Mehrizi, Huysman, & Feldberg, 2017). In this study we build on the premise that micro-foundations of dynamic capabilities in OR activities can be enhanced through different ways, and that there can be many alternatives to analytically enhance dynamic capabilities.

3. Research Design

3.1 Case Method and Site Selection

The case study is a valuable method for exploring practiced-based problems such as this, where the experiences of actors is important and the context of action critical. Given that the specific aim of this research is to explore the use of analytics in dynamic, uncertain conditions, the case study is highly suitable as it facilitates engagement with those 'living the case' (Denzin & Lincoln, 2008). Prior to engaging in the study, the researchers were aware that many of the modifications and sophisticated dynamic capabilities and the associated uses of analytics would be quite subtle, and in some cases difficult to detect and verify. In such cases, exploratory research using methods such as case studies can help identify and focus on such phenomenon (Yin, 2009). The researchers can unearth micro-foundations of sensing, seizing and transforming, and elucidate specific, subtle and perhaps complex roles that analytics played in those capabilities. The case study approach is also beneficial where control over behaviour is not required or possible as data can be collected through observation in an unmodified setting (Yin, 2009). Table 3 provides a brief description of the cases studied, the OR techniques and data tools used, and the job titles of the users of these techniques and tools who were interviewed. Pseudnyms have been used to protect case anonymity.

Case Description	OR Techniques and Data Tools	Users Interviewed
ITSolutions: Global provider of technology solutions services.	▪ Optimisation and scheduling are used to manage 100,000 Peripheral Component Interconnect (PCI) configurations per day. ▪ Statistics and spreadsheets are used for defect detection and root cause analysis in software that processes USD450 million worth of sales each quarter. ▪ *Tableau* is a data visualisation tool that is used for transforming data into interactive dashboards.	▪ IT Director ▪ Portfolio Manager ▪ Technical Project Manager ▪ Project Manager ▪ Financial Controller
DigiTech: Provide bespoke cloud and network computing services.	▪ Spreadsheets, statistics and scheduling is used to manage the review of 1,200 patches (code) per software release ▪ Lead an open-source project involving 40 companies and 110 software developers. ▪ *Microsoft PowerBI/EasyBI* tools provide interactive visualisations to manage software defects.	▪ Software Programme Manager ▪ Technical Programme Manager ▪ Project Manager
Global Foods: Serve international markets with prime meat and convenience foods.	▪ DSS and strategic planning tools are used to manage €1 billion annual turnover. ▪ Spreadsheets and scheduling are used to manage the production of over 900,000 animals each year. ▪ An enterprise resource planning system is used for data capture in meat-processing facilities across Europe.	▪ CEO ▪ Financial Director ▪ Business Information Manager
SoftCo: Develop software for software development and project management.	SoftCo development platforms enable: ▪ Real-time development optimisation ▪ Forecasting of defect rates and accurate estimation of completion times and delivery dates ▪ Analytics is a key differentiator of SoftCo's development platforms	▪ Project portfolio manager (across 22 teams) ▪ 3 Scrum team leads
SP Bank: Part of the Norwegian alliance bank.	▪ DSS are used to analyse 30M daily transactions to determine credit score ratings, risk management, and credit limits. ▪ Forecasting is used to determine potential business opportunities based on credit card transactions. ▪ Statistics are utilised to formulate personalised services to customers based on transaction history and demographics.	▪ Head of Credit Risk and Analytics ▪ Data Analyst
CellTalk: A Norwegian multinational telecommunications company.	▪ DSS are leveraged to provide personalised offerings to customers based on use patterns. ▪ Strategic planning tools are leveraged to determine future investments in infrastructure based on mobility data. ▪ Forecasting is used to estimate network traffic based on data from 2-million devices across 29 countries and is collected every 10 seconds.	▪ VP Analytics and AI ▪ Senior Data Scientist ▪ Senior Research Scientist
Aid International: An international humanitarian aid program.	▪ Optimisation methods are used to determine optimal ways of selecting and deploying fundraising campaigns. ▪ Strategic planning tools are used for donor recruitment and engagement strategies (worth €520M revenue in 2016). ▪ Analysis of data from over 500,000 donors and 2,600 campaigns is used to inform fund raising current and future fundraising strategies.	▪ Digital Strategy Director ▪ Consultant ▪ Senior Analyst
LinkOne: A Norwegian power and fibre-based internet service provider.	▪ Simulation and forecasting is used to determine effects of changing weather patterns on infrastructure and devices. ▪ DSS guide deployment of technical staff on a proactive basis on nodes that have high risk of failure. ▪ Data is captured from log messages of over 3,000 network devices from the Norwegian Meteorological Institute.	▪ Head of Network Engineering ▪ Head of Systems and Operations ▪ Data Analyst

Table 3: Description of Cases and Interviewees

Case	Purpose	Sensing	Seizing	Transforming
ITSolutions	Predictive analytics to identify potential production design issues.	Early identification of sub-optimal configurations.	Mobilising resources to achieve optimal configuration.	Re-engineering processes to achieve optimal configurations.
DigiTech	Diagnostic and prescriptive analytics to understand defect patterns and efficient resource allocation.	Understanding defect patterns and inefficiencies in the allocation of resources.	Building competencies to minimise defects and improve team performance.	Reconfiguring and alignment of organisational capabilities.
Global Foods	Business analytics to monitor meat production yields and align with sales forecasting based on international trends.	Identifying suppliers of low-yield animals and patterns in consumer consumption.	Formalising new partners in value chain and building responses to customer needs.	Reconfiguring internal processes to maximise yield and managing knowledge about customers and processes.
SoftCo	Customer analytics to continually align product features to processes and behaviours of development teams.	Sensing subtle changes in developers' desired behaviours – use and non-use of each feature.	Determining ways the development platform can be modified to align or enable such behaviours.	Developing business model, development and roll-out of modified features to enable behaviour.
SP Bank	Understanding customer behaviour and align product offerings to their changing needs.	Sensing trends in customer credit card and repayment patterns.	Assessing risk based on customer behaviour.	Developing approaches for engaging customers.
CellTalk	Developing better relationships with customers and offering personalized services and pricing schemes.	Recognise customer requirements and identify areas for improved service offering.	Determining customer profiles and optimal service offerings for their needs.	Develop customised packages and improve service quality and automate customer service.
Aid International	Increasing donators' engagement to the organisation and improving campaign effectiveness.	Identifying customer profiles and donation attitudes.	Formulating strategies for attracting donors and non-donors.	Developing personalised campaigns and customer-built donation packages.
LinkOne	Developing proactive mechanisms for identifying network faults and reducing/preventing downtime on network.	Identifying devices on the network that are in high risk of failing.	Deciding how to prioritise repairs and purchase network devices.	Implementing maintenance procedures for real-time network management.

Table 4: Specific Analytics Use Cases Studied

3.2. Data Collection and Analysis

Data were collected over an 18-month period from January 2017 to May 2018. Data collection was primarily personal face-to-face interviews, a technique well suited to case study data collection, and particularly for exploratory research such as this, as it allows real-time clarification, expansive discussions which illuminate factors of importance (Oppenheim, 2000; Yin, 2009), and reflexivity (Rubin & Rubin, 2011; Wengraf, 2001) by allowing the researcher to follow up on insights uncovered mid-interview and adjust the interview content and schedule accordingly. Interviews lasted between 40 and 120 minutes. The interview protocol was based on the three dynamic capabilities and six 'V's of analytics (Fig. 1). In this study, semi-structured interviewees with 26 key decision-makers at the cases studied who rely on OR techniques and analytic capabilities for the purpose of strategic and operational planning. Interviewees were selected using role-based sampling (Ikonen, Kettunen, Oza, & Abrahamsson, 2010) and their role, industry experience and knowledge of business analytics varied across the cases. To aid analysis of the data after the interviews, all were recorded with each interviewee's consent, and were subsequently transcribed, proof-read and annotated by the researchers. In cases of ambiguity, clarification was sought from the corresponding interviewee, either via telephone or e-mail. This approach afforded rich access to multiple data sources (Coghlan & Brannick, 2014) that are pertinent for longitudinal studies and it provided opportunities to obtain a detailed understanding of the empirical setting (Adler & Adler, 1994). This data was supported by supplementary data sources that included analytics screenshots and reports, associated meeting minutes, and relevant e-mail communications. These sources were used to add context to the analysis of the cases studied and were analysed using the open and axial coding techniques.

Data analysis: This was conducted through a number of steps. Each of the data sources was analysed using open and axial coding techniques proposed by Strauss and Corbin (1998) (see examples in Appendix A and B). Coding began by looking for evidence of the constructs identified by dynamic capabilities (e.g. sensing, seizing, transforming) and the characteristics of big data (e.g. 6 Vs). The authors jointly coded the interview data to identify emerging novel themes and axial codes. *Open Coding:* Open coding is 'the process of breaking down, examining, comparing, conceptualising, and categorising data' (Strauss & Corbin, 1998). Glaser (1992) argues that codes and categories should emerge from the data, while with Strauss and Corbin (1998) these are selected prior to analysis. The approach adopted in this study is more akin to the latter, where the data sources and subsequent analysis was based on the dynamic capabilities/6 V's model (Fig. 1), and specifically the constructs underlying each (e.g. sensing, seizing, transforming). These provided a list of 'seed categories' (Miles, Huberman, & Saldana, 2013b) to structure data collection and the open coding stage of data analysis. *Axial coding:* Axial coding is defined by Strauss and Corbin (1998) as a set of procedures whereby data are put back together in new ways after open coding; whereas open coding fractures the data into categories, axial coding puts the data back together by making connections between the categories and sub-categories. As the data were coded, theoretical questions, propositions and code summaries arose. These were documented in analytic memos (Miles, Huberman, & Saldana, 2013a) to aid understanding of the concepts being studied and to refine further data collection. Memos can take many forms (e.g. diagrams, text narrative, propositions) and act as the pivital point for comparison and emergence, through which constant comparison is achieved (Charmaz, 2006; Glaser & Strauss, 2017). Constant comparison was used to analyse data from different standpoints (Birks, Fernandez, Levina, & Nasirin, 2013), from which a number of analytics micro-foundations were identified for each construct (e.g. sensing, seizing, transforming), followed by the emergence of six propositions. Miles et al. (2013a) offer advice on effective analytic memos, and these practices were followed where possible.

As categories emerged follow-up interviews were arranged with all the original interviewees to elicit further, richer, more focused information. This was done to confirm, extend, and sharpen the evolving list of categories. As categories became integrated, further data collection did not tend to cause any additional categories to emerge, but rather reinforced those already in existence. At this point, the categories were deemed to be 'theoretically saturated' (Strauss & Corbin, 1998), and data collection ended. Across all phases, to improve the reliability and repeatability of the research, an, 'audit trail' was sought from data collection through to the drawing of conclusions. Venting was used, whereby results and interpretations are discussed with professional colleagues to avoid the problem of what Kaplan and Duchon (1988) call multiple realities.

4. Findings

The business value of business analytics is dependent on an organisations ability to leverage the Vs of data to identify opportunities and threats (sense), mobilise resources to capitalise on opportunities and threats (seize), and reconfigure tangible and intangible resources and capabilities for the continued renewal of the organisation (transform). This section identifies key micro-foundations and the associated Vs that enable organisations to build dynamic analytic capabilities.

Sensing

The eight cases studied revealed five analytic sensing micro-foundations that generate opportunities for value creation. These are, (i) *sentiment sensing*, (ii) *non-customer sensing*, (iii) *internal process sensing*, (iv) *external process sensing*, and (v) *customer segmentation*. A description of each micro-foundation and the associated Vs that underpin them are listed in Table 5.

Sensing: Analytics micro-foundations	**OR techniques**	**Volume**	**Velocity**	**Variety**	**Veracity**	**Vari-ability**	**Visual-isation**
Sentiment sensing: Identifying and understanding the sentiment of staff, customers, and competitors. *(Global Foods, DigiTech, SoftCo, CellTalk)*	Spreadsheets Statistics	X	X	X	X	-	X
Non-customer sensing: Identifying and understanding non-customer's needs. *(Aid International)*	DSS Statistics	X	X	X	X	-	X
Internal process sensing: Identifying internal inefficiencies, quality controls and best practices. *(Global Foods, DigiTech, ITSolutions, SP Bank, LinkOne)*	Spreadsheets Scheduling DSS	X	X	X	X	-	X
External process sensing: Identifying external inefficiencies, quality controls and best practices. *(Global Foods, DigiTech, ITSolutions, SP Bank)*	Spreadsheets Scheduling DSS	X	X	X	X	-	X
Customer segmentation: Identifying and understanding the needs and requirements for different sub-	DSS Statistics Forecasting	X	X	X	X	-	X

populations. *(Aid International, SoftCo, CellTalk, SP Bank)*							

Table 5: Sensing Micro-foundations and Key Vs

Sentiment sensing: Sentiment analytics is critical to Global Foods, SoftCo, and CellTalk as it enables them to identify positive and negative customer and staff sentiments well before other signals. For example, during daily use of SoftCo development platforms, they also use their product's dedicated wikis and discussion boards to examine sentiment. They have shown statistically that the use, volume and content of both mechanisms identify potential dissatisfaction long before any market research or any other form of analytics. DigiTech use sentiment analysis to sense the effect of discussions during a review of software code between members of an open source project, which involves 40 companies and 160 software developers. Fig. 2 shows the sentiment of software developers who are responsible for reviewing the quality of software code during a release cycle (28th Feb – 4th May). The benefit of this micro-foundation is that project managers can sense the effect of negative sentiment that may lead to delays in deploying new software, or worse, the review community rejecting the new code. For example, this micro-foundation enables project managers to not just identify outliers (blue box in Fig 2) but also to be able to drill down to identify who is being extremely negative, the time of day/night that the review was conducted. Then they can engage with the individual to understand why their sentiment is extremely negative (use of language, work related issues etc) and to establish what time (morning, afternoon) and days of the week is most suitable for conducting code reviews.

Fig. 2. Sentiment Analysis During a Release Cycle

Global Foods sense customer sentiment by analysing Twitter datasets. As a result, this micro-foundation enabled Global Foods with the opportunity to sense (i) customer sentiment of a new or existing product, (ii) ideas for product and service innovation, (iii) how customers compare products with its competitors, and (iv) marketing needs for specific customer segments/regions.

Non-customer sensing: Aid International use their data analytics capabilities to sense donor behaviour and leverage it to uncover non-customers that could potentially be a large source of donations. The sensing involves sophisticated clustering analytics based on data provided by donors through their registration forms, as well as data on the types of campaigns they participated in, media through which this was done, location, and other available information that can be inferred from the data. Based on this data they develop donor personas using design thinking and empathy mapping (Liedtka, 2011) to better understand population groups that are currently within their scope of donors. After defining personas and their attributes, the design thinking process is used to uncover non-customers and define their world-view and requirements. This is done by identifying major population groups that are not within their sample, and through design thinking processes develop their personas to be able to better approach them and understand their needs. Through this process, Aid International could sense the needs and worldviews of its current customer base, but more importantly uncover major population groups that have not been targeted or engaged in campaigns. To be able to accurately estimate donor and non-donor clusters, it is important for Aid International that they aggregate large volumes of data from different sources (i.e. campaign data, donor information, social media, website interaction etc.), and monitor changes in personas in a frequent manner. An early estimation made by Aid International is that through this form of non-donor sensing they could develop strategies for attracting 75% new active donors.

Internal process sensing: Five cases studied use business analytics to sense opportunities to reduce or process issues. ITSolutions, for example, track unresolved defects. Fig. 3 shows expected spikes of 9%, 16%, and 8%. A spike of up to 9% could be acceptable and expected as it might be very difficult to capture defects with minimal impact (i.e. end user issue) before code goes to production. However, as the 16% spike is above the acceptance threshold, project managers can engage with the quality team and mitigate a plan to reduce or prevent high impact defects (i.e. blocking real-time payments).

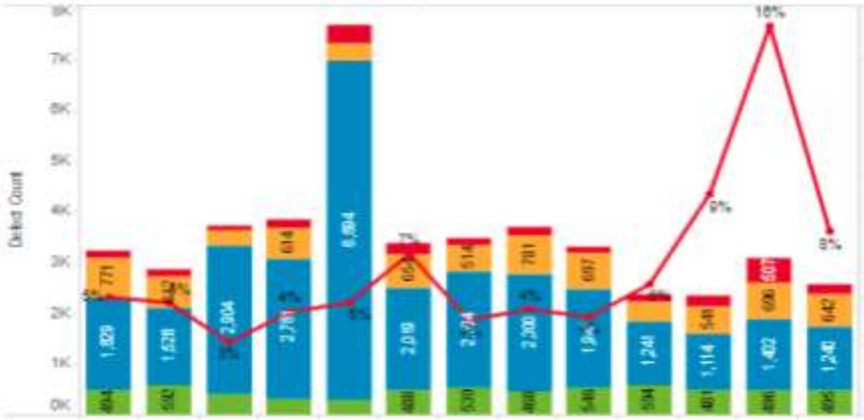

Fig. 3. Predicting Defect Rates

LinkOne use analytics to sense the status of their internet infrastructure from large volumes of data originating from over 3,000 routers, switches, and other network devices. An example of such proactive sensing is in cases of high external temperatures which have been significantly correlated with fault occurrence (Fig. 4). LinkOne uses predictions from the meteorological institute, in combination with node temperature data, and applies stochastic dynamic programming methods to sense which nodes within their network are at the highest risk of failing. Fig. 4 shows with the red line the predicted temperature of a node in the network in relation to weather forecast. If values exceed a certain threshold then alarms signal to notify technicians that with a high degree of confidence a node is likely to fail. The business analytics have enabled LinkOne to be able to predict with a 95% confidence interval which devices are likely to fail within the next 12 hours.

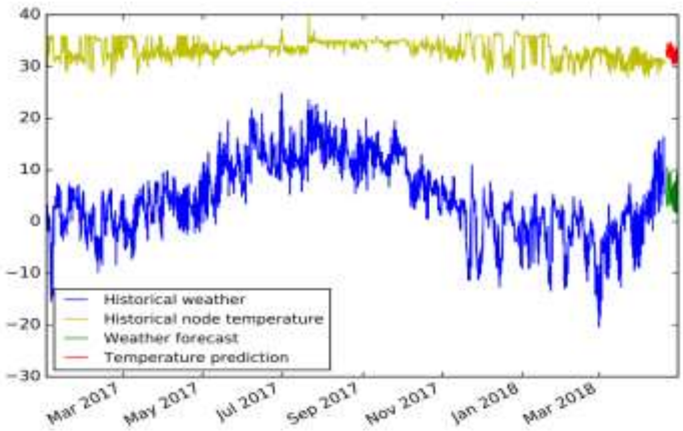

Fig. 4. Temperature History and Predictions for a Node in a 12-hour Period

External process sensing: Emerging threats in the financial environment as well as trends in specific product and service types is a key component of being capable to reposition offerings for credit card companies such as SP Bank. The company monitors internal data of its customers such as spending categories and amounts, times of repayment, method of transaction, as well as external data such as company performance indicators and balance sheets, money market data, as well as credit rating agency information amongst others to sense discontinuities in the external environment. By developing such strong sensing capabilities based on analytics, SP Bank can then adapt according to emerging threats and opportunities, as well as provide aggregated information to other companies under the alliance. An example of such external process sensing in SP Bank is by developing fraud management and prevention mechanisms based on analysis of spending patterns. Through this way SP Bank can ensure that its customers, whether individuals or companies, are not subject to fraudulent actions. In addition, the variety of data sources and the velocity by which it is analysed ensures that data is validated from multiple sources, and so discontinuities are sensed with the highest possible accuracy. This is key in the financial industry where minor deviations or negative impacts on customer loans and accounts can have high negative consequences.

Customer segmentation: Being able to segment and sense the needs of different segments through analytics was highly valuable to CellTalk, SoftCo, SP Bank and Aid International. As an example, swathes of developers stopped reporting and using parts of SoftCo's platform. Initial analysis suggested no pattern, but re-analysis by segment revealed that these irregular behaviours were largely due to a single segment of open source developers- all of which subscribe to certain, subtle philosophies regarding commercialisation and ownership. Identifying and developing functionality targeted at this segment has *"increased eight-fold the use of [SoftCo's platform] amongst open source communities"* (SoftCo CIO).

Seizing

Four core analytic micro-foundations were identified with respect to seizing: (i) *real-time process orchestration*, (ii) *dynamic resource allocation*, (iii) *customer risk profiling*, and (iv) *prioritising target customers*. A description of each analytic seizing micro-foundation and the associated Vs that underpin them is listed in Table 6.

Seizing: **Analytics micro-foundations**	**OR techniques**	**Volume**	**Velocity**	**Variety**	**Veracity**	**Vari-ability**	**Visual-isation**
Real-time process orchestration: Translating strategic KPIs into operational metrics to guide actions. (Global Foods, LinkOne, SoftCo)	Spreadsheets DSS	X	X	X	X	X	X
Dynamic resource allocation: Using real-time data to inform resource allocation. (Global Foods, DigiTech, ITSolutions, CellTalk, Aid International, LinkOne)	Forecasting Scheduling	X	X	X	X	-	X
Customer risk profiling: Deciding appropriate ways of handling customers based on risk profile. (SP Bank)	Forecasting DSS Statistics	X	X	X	X	-	X
Prioritising target customers: Developing engagement strategies for customer segments with the highest return (CellTalk, Aid International, SP Bank)	Spreadsheets Statistics DSS	X	X	X	X	-	X

Table 6: Seizing Micro-foundations and Key Vs

Real-time process orchestration: SoftCo analytics shows that functionality speed of +- 1.4 seconds negatively affects developers' decision to use or abandon that functionality. SoftCo's dashboards are therefore designed to re-orchestrate what the developer sees in 1.4 seconds or less. If a developer hesitates or has to wait for data to load for longer than this period on more than one occasion, then the platform re-orchestrates the display process to prioritise this activity and ensure the third display loads in less than that time window. According to SoftCo's CIO "developers time is their most precious asset and so a single focus on optimising their time has established our reputation in the market". Prior to developing this micro-foundation at ITSolutions, the impact of defects was significant. A "Severity 2" undetected defect costs $800,000 in lost revenue and unplanned overtime. Fig. 5 shows the frequency of defects (and root cause) classified as Severity 2 during November. The micro-foundation provides an aggregate of Severity 2 defects across teams and productions environments, which is not possible with non-analytic tools such as Kanban. Having real-time access to the root cause of an accumulating defect enables project managers to promptly re-orchestrate processes in order to reduce 'pro-action' time (the time difference between the defect create time and defect changed time) and 'reaction' time (the time difference between the defect create time and closed time) to resolve defects.

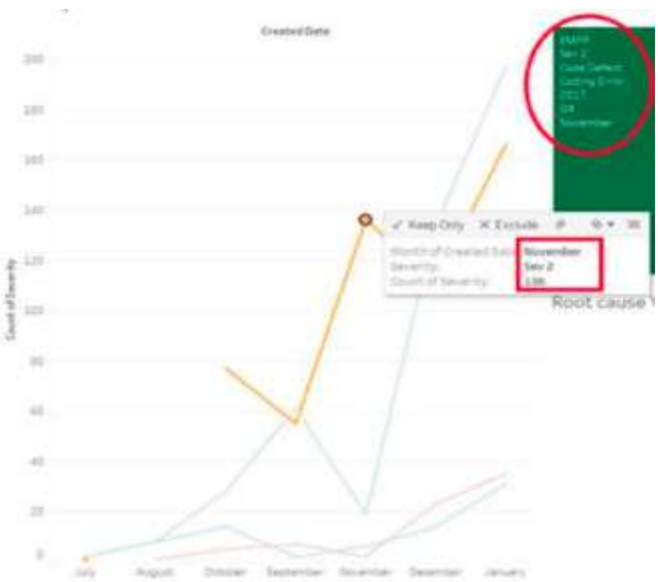

Fig. 5. Real Time Analyses of Root Causes of Defects

Dynamic resource allocation: LinkOne uses predictive analytics to identify network areas that are particularly vulnerable to fault occurrence. These analytics utilise national meteorological institute predictions, as well as data from network nodes such as, traffic rate, battery life, and temperature. This allows dynamic assignment of maintenance tasks. For example, when high temperatures, heavy rain, or strong winds are predicted, they are able to schedule the sites that personnel will visit to perform maintenance. To develop this capacity, LinkOne has used several techniques including machine learning, with a training sample of historical data of over 2 years. The accuracy of predictions and the ability to efficiently calculate the areas of highest risk and attend to them is a result of organisational changes that are revolved around business analytics. Fig. 6 shows optimal replacement strategies of batteries in nodes by temperature effects and suggests replacement schedules for reducing downtime and costs in a prioritised way. For instance, the green line demonstrates that temperatures are predicted to rise after day 40 (bottom part of figure), then the battery lifetime expectancy has a steeper slope than previous days and thus requires more frequent changes (top part of graph indicated by spikes). This allows LinkOne to perform dynamic resource allocation based on predicted events and calculate spending for replacing equipment ahead of time.

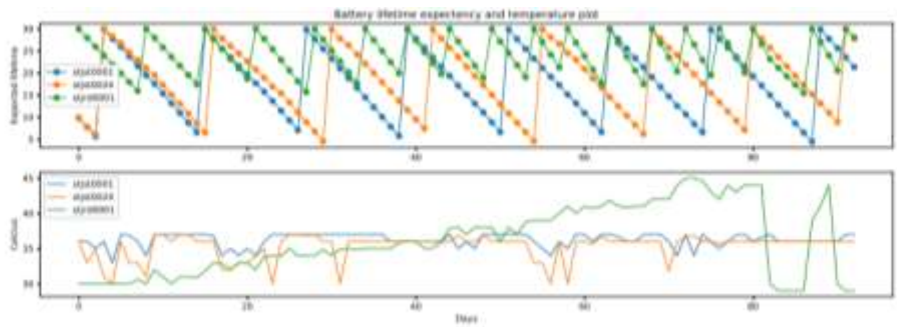

Fig. 6. Decision Plan Based on Temperature, Battery Characteristics, and Cost Values

Customer risk profiling: SP Bank has developed dynamic customer risk profiling techniques of repayments on their credit card debts. These customer profiles are updated automatically and dynamically with every new transaction data point. Various forms of data including the date of repayment, type of transaction, historical data, demographic information, location of transaction and social media data are leveraged to make personalised risk scores and decide credit limit for future customers. Risk profiles can be generated within minutes for new or existing customers of the bank, and the outcomes are presented to employees that handle interactions with customers providing them with very detailed insight. Based on this information a risk assessment value is calculated which dictates the amount and type of credit card and loans one can receive in a much more precise manner. Through appropriate visualisation means these analytics enable front-end employees to make real-time decisions about each customer risk and has led to a reduction of the time needed to create risk reports, while at the same time increasing prediction accuracy. This way of performing risk profiling has enabled SP Bank to attract and retain more of its customers by providing services much faster while at the same time reduce risk by making a more thorough assessment of its potential customers.

Prioritising target customers: Aid International has used analytics on their campaigns to associate customer profiles and their donations towards specific types of campaigns and their profitability. Data from campaign platforms such as TV, social media, third-party websites, and gamified applications, in combination with exact donation amounts from donors and their profile information, enables the organisation to determine the target groups that are most profitable and the mediums and types of campaigns that work most effectively (see Fig. 7). Aid International can also prioritise which campaign channels and types of content appeals most to the selected donor group. Now marketing executives follow the insight produced by business analytics when making decisions about where and how much to spend on different marketing campaigns and in relation to the groups of donors they wish to attract and engage. Analytics has dramatically increased accuracy and removed potential sources of manager bias resulting in an increase of Return of Investment (ROI) in marketing campaigns by 17%.

Fig. 7. Average Donations and Number of Donors by Campaign

Transforming

To ensure that business analytics delivers sustained business value, it is critical that organisations quickly transform their existing mode of operation (organisation, process, people, technology) to adapt to the changing competitive landscape. The cases studied developed four key analytic transforming micro-foundations that enable them sustain business value, namely, (i) *temporal process reconfiguration*, (ii) *developing new business models and services*, (iii) *reconfiguring marketing approaches*, (iv) *reconfiguring operational inefficiencies.* A description of each analytic transforming micro-foundation and the Vs that underpin them is listed in Table 7.

Transforming: **Analytics micro-foundations**	**OR techniques**	**Volume**	**Velocity**	**Variety**	**Veracity**	**Vari-ability**	**Visual-isation**
Real-time process reconfiguration: (Global Foods, DigiTech, ITSolutions, SoftCo)	Spreadsheets Scheduling	X	X	X	X	-	X
Developing new business models and services: (SP Bank, CellTalk)	Forecasting DSS	X	X	X	-	-	X
Transforming marketing approaches: (CellTalk, Aid International)	Scheduling Statistics	X	X	X	X	-	X
Reconfiguring operational inefficiencies: (CellTalk, ITSolutions, SP Bank, LinkOne)	Scheduling DSS Statistics	X	X	X	-	-	X

Table 7: Transforming Micro-foundations and Key Vs

Real-time process reconfiguration: As the environments of the cases studied is dynamic, volatile and continuously changing, having the analytic capability for real-time process reconfiguration is essential for Global Foods, SoftCo, DigiTech, and ITSolutions. SoftCo have established a ‘pomodoro’ time management technique across 105 projects and 600 developers where all are synched into 25-minute pieces of work. Because of this technique, if analytics data shows an emerging problem for any team or number of teams, the 600 developers can reallocate themselves across teams to respond to such issues at 25 minutes notice. Architectural errors were a notable example - the rarity of architects (6 in 612 staff) and the severity of architectural issues, means that such issues can be particularly debilitating if unresolved. Historically, project managers at ITSolutions manually calculated ‘cycle time’ (time spent by project teams working on a user-requirement) using basic spreadsheets to assess the performance of thier software development teams. However, embedding the metric within the code management tool provides real-time access to identify spikes in cycle time that can delay development. This micro-foundation enables project managers to be responsive to unplanned events (developer on sick leave) and minimise its impact on the software development process.

Developing new business models and services: The use of analytics in SP Bank has sparked new business models and several new services, including the provision of consultancy to third parties on the potential of success or failure of future investments. Specifically, for individual entrepreneurs that wish to start their own company, SP Bank uses analytics to provide insights on financial potential, factoring in the demand in the specific market, the location of proposed stores, appropriateness of business plan, and financial consulting. SP Bank uses large volumes of data from several different sources to deliver accurate analytics and builds on real-time information to produce precise assessments of the financial viability of new ventures. Due to the nature of the new business services provided, it is important to have updated information about the current status of the market in terms of potential competitors and rival products/services. As a result, SP Bank has been able to leverage their business analytics to expand their activities and develop new channels of revenue.

Transforming marketing approaches: CellTalk has been able to harness the power of social media analytics to detect best practices and methods for marketing approaches. The company in 2016 acquired Tapad, a marketing technology firm specialised in developing personalised marketing campaigns. This acquisition and the integration of know-how, has led to the development of advertisement spots, color-coding of images, presentation of content, and use of social media depending on individual customer preferences. By delivering a high degree of personalisation in marketing campaigns, CellTalk has managed to position itself as the largest telecommunications provider in the market. Such personalised marketing campaigns have led to approximately 31% more spending by consumers and a significant increase in customer satisfaction. Data-driven approaches have fundamentally altered the way marketing strategies are formulated and the way they are deployed.

Reconfiguring operational inefficiencies: The delay between identifying a fault in the network, localising it, orchestrating local repair employees, and fixing it was an issue that LinkOne had struggled with since their establishment. Due to the analytics function, each local station now receives automated alerts of network nodes that are at high risk of failure. Service personnel are equipped with portable devices that give them real-time information and prioritised tasks for proactive maintenance. This insight has significantly reduced time needed to fix issues and has sliced staff overtime cost by 14% by pre-empting and preventing failures.

5. Propositions

In this section we provide six propositions based on a cross case and cross theme analysis (sense, seize, transform). The propositions demonstrate that business analytics have different levels of relevance for companies when developing dynamic analytic capabilities to sense, seize, and transform opportunities.

Proposition 1: Vs need to be adjusted across sensing, seizing and transforming to maximise value. Previous research generally tends to analyse the value of a particular V. However, this study shows that a particular V may add more or less value as one moves from examining sensing to seizing to transforming in a particular context. For example, ITSolutions teams draw on large volumes of data from a variety of sources such as Instant Messaging (IM) and digital Kanban boards to sense opportunities related to software quality (defects). Project managers respond to between 30 and 40 IMs during an 8-hour shift. The volume of text in an IM can range from a 10 to 100 lines, depending on the urgency and complexity of the request. However, when seizing these opportunities, the volume and variety of data was at times, overwhelming for teams (specifically during a major release) to process and identify root causes of defects. As a result, teams missed defects, or misunderstood the severity of the defect. Similar issues were noted in LinkOne, where the large volume of data received from the networked devices was a core enabler of their sensing capability in identifying nodes with a high probability of failure. However, the same volume proved to be a hindrance when the company tried to develop analytics to rank nodes according to their future risk of failure depending on weather forecasts. LinkOne initially faced the problem of a lack of human resources capable of conducting such analytics on large volumes of data, and insufficient processing power to accommodate such analyses. These circumstances led the company to seek guidance from experienced analysts at the Norwegian University of Science and Technology, who were also able to provide the necessary hardware infrastructure and processing power to execute such analyses. This proposition therefore suggests that, in order to maximise value, organisations need to adjust the Vs when moving from sensing to seizing to transforming an opportunity. SoftCo's developer platform illustrated this, where developer teams can customise the platform to slow down the speed of data or turn on and off selected data sources as and when these Vs detract from value.

Proposition 2: Siloing or lack of alignment between OR tools or techniques and Vs can affect overall value of analytics. As data was collected for this study, it became apparent that those collecting the data and those being interviewed often talked about analytics generally. For example, many interviewed in SoftCo referred to "the team facing high volumes of real-time defect data" or there is a real focus of high veracity data in SoftCo. However, it became apparent that various OR tools may exhibit very different characteristics, which often restricted or reduced the possible value from micro-foundations. As can be seen across the three sets of micro-foundations (Tables 5, 6, and 7), one micro-foundation was often supported by only one OR tool in each case, and so, while the overall volume, velocity or other may have been high in that case generally, the specific OR tool may not. Further, different OR tools are used in the same case across the sensing, seizing and transforming capabilities, and there was evidence to show that value may be lost if there is a disconnect between the OR techniques across these capabilities. Interviewees across all cases talked about their use of OR tools as separate tools rather than a collective suite of interlinked tools. It emerged that OR tools were frequently used in isolation from other tools and techniques, which did affect the overall value of analytics within each case studied. Evidence of siloed thinking and siloed usage occurred within and across functions, which limited the value of analytics. For example, at ITSolutions, quality control charts are used to determine if a process (production line) requires calibration in order to ensure variations in the outcome do not occur. Historically, these charts were manually created using spreadsheets for a specific function, did not provide root cause information, and were vulnerable to human error. Using powerful real-time analytical tools such as Tableau provide a single point of truth for teams across functions.

Proposition 3: Value of analytics in OR is increased when there is temporal alignment (i) across Vs and (ii) across sensing, seizing, and transforming. While micro-foundations add value in various ways, analysis showed that the timing of these is crucial. Alignment 'across Vs' refers to the timing of the various Vs associated with a micro-foundation. SoftCo's developer platform aligned volume, and velocity of defect data with veracity, by ensuring that a full unit test was run every time a potential defect was raised. This ensured that the time between the volume and velocity of data coming in, and the assessment of its veracity was milliseconds. Prior to this, data was often unverified and thus developers had taken subsequent incorrect actions that were often impossible to identify or remove if verification was even minutes after the incoming data. Misalignment of Vs across sensing, seizing and transforming was also identified. In Global Foods as administrative staff did not work weekends, they were required to update the excel sheets and DSS tool every Monday morning to account for production and sales issues that occurred over the weekend. As a result, reports were not provided to key-decision makers until late Monday or even Tuesday. This misalignment of OR techniques and analytic tools resulted in time-delays and missed opportunities across production and sales. More concerning was that interviewees reported that the veracity of data was often compromised as the data entry person was under pressure to 'catch-up'.

Proposition 4: Perception can impact use and value of OR analytics. An interesting phenomenon related to different stakeholder perceptions of analytics. Key decision-makers in ITSolutions disregarded any data from the coding platforms as lacking veracity, favouring "anything Excel" such as time-sheets completed by staff as much more trustworthy. This is despite the fact that the former is based on objective analysis of the amount of time spent working on that code versus the subjective and potentially biased self-estimation by individuals. Although project teams were required to complete daily time-sheets which were then used by the finance team for billing the client, project managers reported that they frequently had to follow up with individuals at the end of a release cycle to retrospectively complete timesheets that were incomplete or not completed at all. Yet, the data to calculate cycle time (time spent by a team working on a specific user-requirement) was available within the coding platform and used by project teams to manage their workflow. In Digitech, project teams initially used different versions of the same business analytics tool (e.g. PowerBI, EasyBI) for defect management and reporting. However, as EasyBI can only connect to a single data source (code management tool) it only shows defect patterns and not outliers, which is where the root-cause of major defects occur. While PowerBI uses multiple data sources (Variety) that capture outliers, which in turn provides more accurate results (Veracity) and more meaningful representations of the data (Visualisation) for data-driven decisions. As a result, EasyBI was perceived by a manager as "a glorified spreadsheet and that it did not add value when reviewing projects that are worth over €1.2 billion in revenue to the company". In Global Foods, managers frequently questioned the veracity of factory floor data e.g. time spent butchering meat, and so production managers used clip boards to record the data which was then entered in an Excel file for the administration office to aggregate and align with sales data. Although the data was almost always correct, the perception of its veracity created a delay in effective management decisions related to organisation, people, process and technology. There was also clear evidence that different business functions perceived the same data very differently e.g. legal departments taking a prudent, conservative view of analytics data versus those customer-facing staff who were often willing to act on highly questionable data.

Proposition 5: Some Vs have a negative impact on the value added by OR. The Vs of analytics are almost always talked about in positive terms; there is an underlying assumption that an increase in veracity, volume or velocity of data for example, will enhance dynamic capabilities in some way. However, there were many examples across the cases where an increase in Vs detracted from dynamic capabilities. The most common and most impactful examples usually referred to too much volume of data to parse, velocity being too fast, or so much emphasis on veracity that, while positive in one sense, impeded the ability to move quickly and make decisions. LinkOne represents one case. While the data received from their networked devices enabled them to sense identify which had a high risk of failure, the volume of data became a hindrance when attempting to develop predictive analytics and proactively orchestrate maintenance personnel. The large volume of data that is required to effectively predict which devices are in highest risk of failure meant that LinkOne required that significant resources needed to be allocated towards finding optimal ways of turning data into insight. This meant that for a long period of time LinkOne had little to no insight about how to perform proactive maintenance. Similar occurrences are detected also now, where in the attempt to increase accuracy of prediction by incorporating data from streaming services, there are limited resources monitoring the quality of generated insight, thus, having a hindering effect on value. In ITSolutions, real-time data allowed immediate sensing of a problem. However, the incessant automated pings from Instant Messenger (IM) continually interrupted their flow of work, and according to some created a form of Pavlovian conditioning where everyone was on a 'stay alert' response mode even when no pings occurred. Developers then muted the ‘ping’ sound of their own machines and others, only responding to major defects when notified by management, and thus undoing sensing potential of the analytics function.

Proposition 6: Value of analytics in OR increases over cycles of enacting dynamic capabilities. The value of analytics is often assessed over one event or at a snapshot in time. However, this study showed not just that analytics needs to be considered across the capabilities of sensing, seizing and transforming but over many cycles of these capabilities. Several of the cases showed that initial applications of analytics were poor but that the value increased over time through trial and error. As an OR team lead in SoftCo stated “we keep about 2% of the analytics techniques that we try, and those we experiment again and again to get better”. An ITSolutions executive recalled that many analytics applications are “highly problematic, flawed and so fail outright or are abandoned completely”. An example of this is LinkOne, who initially used data from networked devices to sense potential fault occurrences in their network, conduct proactive maintenance based on insight, and transform resource management based on data-generated insight. LinkOne realised that the capacity to transform their operations was limited by the variety and velocity of data. This resulted in changes to the settings of data transmitted from networked devices, so that they received more relevant and rich data, and thus predict with greater accuracy fault occurrence in the network. These findings indicate that business analytics can serve as higher-order dynamic capabilities, meaning that they operate to enhance and improve existing ways of sensing, seizing, and transforming (Schilke, 2014b). This idea has gained traction in management literature, where there is a growing body of research seeing dynamic capabilities as being in flux (Schreyögg & Kliesch-Eberl, 2007). Understanding how dynamic capabilities emerge and what aspects strengthens their development is critical in the quest of understanding sustained competitive performance in the operational research context (Waleczek, von den Driesch, Flatten, & Brettel, 2018).

6. Discussion

6.1 Contributions of the Study

Research has only now started to address the managerial implications of analytics in the field of OR, highlighting key challenges in eliciting value (Vidgen et al., 2017), or providing deployment frameworks (Hindle & Vidgen, 2018; Vidgen et al., 2017). To date however, little research exists on how analytics can add value for OR activity in turbulent, uncertain and constantly changing competitive landscapes- the place where they are most often needed and used. The over-arching contribution of this study is the introduction of dynamic capabilities as a lens to study the use of analytics in OR. This is achieved in two ways. The first is the identification of 14 micro-foundations, each of which are a means for business analytics to facilitate value through OR-enabled dynamic capabilities i.e. sensing, seizing and transforming (thus answering RQ1). The second contribution is the identification over-arching propositions that may affect the extent to which business analytics facilitate value through OR-enabled dynamic capabilities (thus answering RQ2). Each contribution is now discussed.

Micro-foundations: To date, a number of studies in fields outside OR, suggest that business analytics may have positive effects on a firm's dynamic capability processes (e.g. Côrte-Real et al. (2019); Mikalef et al. (2019b); Mikalef et al. (2019c); Wamba et al. (2017)). However, these studies have not specifically studied an OR context and have also remained at a general, higher-order conceptualisation of dynamic capabilities. This study disaggregates dynamic capabilities into the three constituent components of *sensing* (Table 5), *seizing* (Table 6) and *transforming* (Table 7), with a new set of associated micro-foundations for each. The study found that different micro-foundations are valuable at different phases of the dynamic capability process, and also found that different OR techniques and combinations of techniques add value across the three different stages. This is different to previous research, where studies tend to atusy analytics at an over-arching level or else study one OR technique in isolation; variance in value across phases has not been considered. This study is also the first to analyse analytics-enabled OR under the various 'V' components of analytics. Previously analytics was assessed at an overall level. This study showed the importance of analysing at the more granular 'V' level. Almost all micro-foundations relied on some Vs more than others, each OR technique added value through different distinguishing Vs. This supports Vidgen et al. (2017) contention that the data itself is key to enabling dynamic capabilities, as opposed to just the OR or analytics techniques that draw on that data.

Propositions: The propositions identified (P1 to P6) support the need for an 'umbrella' approach such as that of Hindle and Vidgen (2018), which fuses the implementation of analytics and OR techniques, and recognises that analytics and OR is an "entangled and emergent mix of top-down analysis and bottom-up action" (*ibid*). However, this study adds a number of distinct factors. While Hindle & Vidgen show alignment between analytics and business goals is necessary, this study shows this is not a static activity. Instead, different OR techniques will draw on different features of analytics when sensing change, seizing opportunities and transforming (P1). Analytics may add value at one point in time but not another. Also, even where OR and analytics tools may individually and collectively align with business goals, there may be a lack of alignment between the data the techniques collect and provide to each other to add value (P2), or a lack of synchronisation with which they collect and provide this data to each other (P3). In terms of perceptions of analytics in OR, research has focused on fieldwide perceptions such as Ranyard's (2015) observation of "a noticeable resistance from the traditional OR community" regarding analytics. This study (P4) shows that perceptions of an OR analytics technique and its value will vary by individual and groups (e.g. managers versus technique users, legal versus operations teams). Therefore, we suggest analytics implementation models include steps to elicit and manage diverse perceptions. Another implication of this study is the need to critically examine the value of analytics and particularly each of the Vs in any OR implementation (P5), rather than making an assumption that higher data volume and velocity in OR is unquestionably better. Finally, the notion that the value of analytics in OR increases over cycles of enacting dynamic capabilities (P6) contributes to how we think about the longevity of analytics in OR. Most studies in OR discuss the introduction of analytics as a single project or implementation. However, this research suggests that one must consider the value of analytics in OR over many cycles of change within and across OR projects. In fact, this study shows that the initial value of analytics is usually low or negative, and so the current short-term emphasis may be a contributor to the negativity and resistance to analytics in OR (c.f. Liberatore and Luo (2010); Ranyard et al. (2015)) and others.

6.2 Implications for research

This research elaborates on the existing high level, and relatively sparse theory on the value of analytics in an OR context. The new micro-foundations and the propositions provide a more granular set of components which can be used to develop quantitative models of OR analytics value creation that were not previously feasible due to the relatively low granularity of the analytics concept in previous research. These can then be subjected to hypothesis testing. Second, the introduction of a dynamic capabilities perspective on analytics provides a rich way of conceptualising how organisations can build their analytics capability and transform into a data-driven organisation. Researchers can also use the six propositions as a starting point to studying the complexity of analytics in an OR setting. Finally, Table 8 contains a research agenda emanating from each of the propositions. Researchers may seek to answer these questions in their own research. The agenda also places some structure on future research in the area of analytics and OR, which has been criticised for lacking such structure and coherence to date (Liberatore & Luo, 2010; Mortenson et al., 2015; Vidgen et al., 2017).

P1: Vs need to be adjusted across sensing, seizing and transforming to maximise value.	What are the leading OR techniques and associated tools for effectively adjusting Vs across sensing, seizing and transforming? How can various OR techniques such as optimisation, scheduling and spreadsheet analysis be designed and tailored to support suggest adjustments? What metrics and evaluation can be used to ensure adjustments are effective?
P2: Siloing or lack of alignment between OR tools or techniques and Vs can affect overall value of analytics.	How can organisations achieve and measure alignment between OR techniques/tool portfolio and the over-arching analytics function? How can interdependencies between OR techniques and tools be evaluated, and the resulting impact mitigated? How can these interdependencies be removed or enhanced where desired? What data governance strategies can support or mitigate this lack of OR alignment?
P3: Value of analytics in OR is increased when there is temporal alignment across Vs, and across sensing, seizing, and transforming.	How can temporal alignment be evaluated across (i) within Vs, (ii) across Vs, and (iii) across sensing, seizing, and transforming? How can such alignment be improved and/or optimised? How can organisations effectively develop top-down strategies so outcomes are clearly connected with the required data?
P4: Perception can impact use and value of analytics in OR.	How can the different perceptions of OR and the various Vs and analytics be identified? How can the impact of such differences be identified and reconciled if needed?
P5: Some Vs have a negative impact on the value added by OR.	How can the negative aspects of each V be evaluated? What are the warning signals regarding a potential negative impact of a V on OR activity? How can these negatives be negated or minimised in each context?
P6: Value of analytics in OR increases over cycles of enacting dynamic capabilities.	How do organisations integrate learning outcomes from previous use of analytics in OR? What structures facilitate individual and organisational learning from past analytics OR projects? What are the important elements to consider when scaling up business analytics projects from experimentation to full OR-wide deployment?

Table 8: Analytics in OR - A Research Agenda

6.3 Implications for OR practitioners and managers

OR practitioners now have a guiding list of micro-foundations in Tables 5, 6, and 7, each accompanied by empirical case-based examples, to help evaluate or change their OR tools and techniques to leverage value from analytics. This by no means represents a panacea or entire list. We encourage OR practitioners to use the sensing, seizing and transforming categories as a guiding structure to reflect on what dynamic capabilities are relevant in their context, and to identify and implement other micro-foundations that may be relevant and ultimately more valuable. Third, the propositions highlight the potential significant complexities that practitioners and managers face when implementing analytics-enabled OR in dynamic and uncertain settings, such as perceptions of the same analytics data, the synchronisation of OR activities around analytics data, and critiquing the value of analytics in OR in any given context. The research provides further evidence to support Vidgen et al. (2017) view that business analytics is not a technical project that can be given solely to the IT department. It goes further, however, by showing the deeply embedded connections and tensions between the techniques and tools of OR and those of analytics. It shows deep integration of analytics and OR is necessary and is not resolved by the simple addition of an analytics department or data scientist.

6.4 Implications for OR educators

Similar to practice, OR education has been slow to incorporate analytics, and there have been calls for updated OR curricula (Liberatore & Luo, 2010). This study contributes to this gap in a number of ways, to assist educators in improving their curriculum design and delivery. Firstly, it demonstrates the importance of getting students to think about analytics and OR in the context of a dynamic environment. Currently, OR analytics tends to be through static examples or cases based on a frozen point in time. Educators can achieve this by drawing on the 14 micro-foundations to identify any curriculum gaps and to modify their modules. While it is certain that some of the micro-foundations are being taught in some form across OR curricula, the dynamic capabilities provides a structure for students to assess and understand analytics and OR in terms of how we deal with change, turbulence and uncertainty. Second, while analytics is slowly appearing throughout OR curricula, it is usually as a separate "stand alone" analytics module. However, this study shows the deeply embedded connections and tensions between OR techniques and tools and the techniques and tools of analytics, and therefore shows the importance of not just including analytics, but integrating it into all aspects of the OR curricula. Third, the propositions provide a structure to teach the complexity of combining analytics and OR, e.g. perceptions, critique and synchronisation of analytics for increased value. Finally, the study showed how the value and challenges of various OR analytics techniques differs greatly across contexts. This supports Liberatore and Luo (2010) call for OR analytics offerings to specialise in analytics for a particular industry, problem domain, or business process.

7. Limitations and Future Research

The study adopted an exploratory, case-based approach. There are many benefits to examining temporal factors using quantitative, longitudinal and other research approaches. The research agenda (Table 8) highlights some of these opportunities. Longitudinal studies would be particularly desirable, given it would be somewhat ironic to study the use of analytics in dynamic changing conditions without, at some point, examining the use of analytics either 'before and after' or during such change events. Such longitudinal research would reduce issues such as recall or recency bias which affect much research, but would be particularly insidious where the dynamism and change at play is the very focus of the research. Second, one should not assume all organisations require highly dynamic capabilities. Before adopting the suggestions of this research or taking corrective action, it is important to determine (i) to what extent dynamic capabilities are relevant, and (ii) to what extent analytics plays a role in each. The micro-foundations developed in this study will need to be researched or applied with these trade-offs and complementarities in mind. Finally, this study focused on a unidirectional relationship of analytics as an enabler of dynamic capabilities. Future research could focus on the important reciprocal and symbiotic relationship, whereby organisations engaging in data analytics must have a certain level of dynamic capability; they must be able to sense, seize and transform around emerging and changing analytics tools and associated opportunities, as opposed to just using the analytics function to enable capabilities.

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Appendix A: Examples of coding scheme for micro-foundations (*sensing*)

Code	Subcode	Sample Quote	*Open Code*	*Axial Code*
Sensing	Volume	*Volume is increasing from 1,300 patches last release to 1,700 this. We don't know if 400 patches means 400 or 40,000 lines of code.*	Volume/ Changing	Emerging Factors/Changing relevance of Vs
	Velocity	*Velocity of data is not a priority for us as the pace of change is slow here – 3 to 6 months.*	Velocity/ Relevance	Emerging Factors/Relevant/non-relevant Vs
	Variety	*We have a limited variety of data which limits our ability to sense, seize, and transform.*	Variety/ Relevance	Emerging Factors/Relevant/non-relevant Vs
	Veracity	*Veracity of data is key for our team to constantly improve quality process and stabilise workflow throughout the software development process.*	Velocity/ Relevance	Emerging Factors/Relevant/non-relevant Vs
	Variability	*Volume is increasing from 1,300 patches last release to 1,700 this release, this is a large volume of extra work as we don't know if 400 patches means 400 or 40,000 lines of code.*	Variety/ Changing	Emerging Factors/Changing relevance of Vs
	Visual-isation	*People are using different versions (e.g. PowerBI, EasyBi) to present defect reports. EasyBI just shows patterns of past defects, it does not show outliers, which is where the root-cause of defects occur.*	Visualisation/ Synchronisation	Emerging Factors/ Synchronising to needs of business

Appendix B: Example of coding scheme for propositions: Proposition 2

Sample Quote	*Open Code*	*Axial Code*
It's not in our interest to share best OR techniques and practices with other teams and functions because our performance is measured against them.	Silo use/OR techniques	Emerging Factors/Siloing or lack of alignment
Our OR tools are not integrated with each other because we completed several acquisitions over the past year and are struggling to align our processes and systems.	Silo use/Spreadsheets	Emerging Factors/Siloing or lack of alignment
Any metric that involves people entering data into a spreadsheet is a waste of time. Metrics should be collected and analysed from the code management tools that we use.	Silo use/Spreadsheets	Emerging Factors/Siloing or lack of alignment

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