Avoid being the turkey: How Big Data analytics changes the game of strategy in times of ambiguity and uncertainty

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Abstract

In order for organisations to remain competitive in times of ambiguity and uncertainty, there is a need to detect and anticipate unknown unknowns, also called 'black swans'. When these are ignored they may lead to competitive struggles. In this paper, we build on this view and suggest that big data analytics can provide necessary insights to help change strategy making. Research suggests that ambidextrous organisations should focus on developing and maintaining their dynamic capabilities. Following on from this, we take a dynamic capabilities perspective and propose a theoretical framework to explain the intricacies of big data analytics. This framework explains the ability of organisations to detect, anticipate and respond strategically in ambiguous and uncertain business environments. For a meta-synthesis of 101 cases of big data analytics, we employ a multi-method approach that incorporates Natural Language Processing, semantic analysis and case analysis, allowing extraction and analysis of structured information from unstructured data. Overall, we find evidence of big data analytics helping to detect, anticipate and respond to industry disruption. We offer six propositions about the relationships between the levels of data analytics capabilities and strategic dynamic capabilities. We find that descriptive data analytics improves the capability of an organisation to understand the business context (sensing) and that predictive data analytics aids in the realisation of business opportunities (seizing). This study contributes to an understanding of big data analytics as a dynamic organisational capability that supports strategic decision-making in times of ambiguity and uncertainty. We conclude by suggesting areas for further investigation, particularly in regard to the strategic application of prescriptive data analytics.

Practitioner points

- Big data analytics can be observed as dynamic strategic capability; when implemented well, it can add value to an organisation.
- Descriptive analytics and prescriptive analytics can be valuable tools to help organisations better understand uncertain and ambiguous competitive environments and inform strategic decision-making processes.
- The novel approach of extracting structured information from unstructured data, using semantics and Natural Language Processing (NLP), can offer new insights for organisations.

Introduction

In many business settings accelerated change is the only constant [1]. Organisations that wish to remain competitive must focus on excellence in day-to-day business operations and on detecting, anticipating and responding to disruptive changes [2, 3], and they must do so while demonstrating industry leadership and managing shifting stakeholder behaviours [4]. This ability, coined ‘organisational ambidexterity’ [5, 6], is especially important when facing environmental ambiguity or uncertainty [7, 8]. Environmental ambiguity refers to situations in which relationships are unclear and organisations face ‘unknown unknowns’ [8] or unidentified risks. Uncertainty refers to a changing environment, in which a lack of information makes it difficult to determine the causes and effects of change [8]. Ambidexterity is achieved through so called dynamic capabilities that help organisations understand a changing and uncertain environment [9, 10], which, according to Teece [9], requires an analytical framework. Other scholars have suggested that data can assist organisations in understanding their environment [11, 12]. However, it is yet unclear whether big data analytics is a dynamic capability that offers organisations a competitive advantage. It is this question that we aim to answer with our study.

Already, Christensen and Raynor [13] have argued that a firm is in particular need of achieving organisational ambidexterity when it finds itself in an uncertain environment. Such an environment is characterised by newcomers that are creating better products and services, often by using fewer resources and leveraging technology. Ambidexterity requires organisations to recognise new information and to apply dynamic capabilities while focusing on internal and external challenges [5, 14, 15]. With the increasing diffusion of, emerging, digital technologies, incumbents are being forced out of business, especially in traditionally closed markets [16]. Businesses such as Blockbuster, Kodak and Borders serve as examples of once-successful companies that failed to respond to technological changes [17] such as online film distribution, digital photography and online book retailing. By contrast, newcomers such as Instagram, Netflix and Amazon have taken an entrepreneurial approach to leverage technological opportunities that were ignored or overlooked by others [18]. Christensen et al. [13] discussed how disruptive market innovations originate in low-end markets in which incumbents focus on the most profitable and demanding customers. They also develop in new markets in which disruptors aim to develop early footholds to turn 'non-consumers' into customers. Therefore, to avoid a 'Kodak moment' or, in Taleb's words [19], to avoid 'being the turkey'[1], it is vital to develop the capacity to quickly detect, anticipate and respond to market disruptions and competitive threats.

[1] Taleb [15, P40] uses the Thanksgiving turkey as metaphor for what can happen if an organisation fails to understand and prepare for a changing environment. 'A turkey is fed every day and every feeding will firm up the bird's belief that it is the general rule of life to be fed by friendly members of the human race 'looking out for its best interests'.' Until on the day before Thanksgiving, something unexpected happens to the turkey.

As ‘right answers can’t be ferreted out’ [20, P7], recognising technological market disruption in a complex context is no easy feat [21]. Often, disruptive innovations go unnoticed until it is too late [22]. Taleb [19] labelled such disruptors ‘black swans’—or unknown unknowns. These outliers have an extreme effect and retrospective predictability, but are unappreciated when they are first discovered. Black swans result from the interaction of chance, environmental circumstance and decisions made in an environment in which a lack of information limits an understanding of the consequences of those decisions—that is, an ambiguous and uncertain environment [23]. For example, the astronomer Clifford Stoll [24] famously predicted that the internet was a ‘fad’; yet, in hindsight, the internet has facilitated a ubiquitous capacity to communicate across time and space, and has become the catalyst for the creation of societies and businesses constructed around organisational and personal networks [25].

A black swan that is currently unfolding is the blockchain; its effect on global economies and organisations remains unknown, yet it has been predicted to greatly disturb economies and organisations [26, 27]. Some researchers suggest that entrepreneurial thinking allows organisations to better detect the emergence of black swans [28, 29]. Others, such as Taleb [19], have argued that, while access to more information may prevent organisations being surprised by black swans, information alone is not enough to enable adequate responses. Decision-making processes also affect the ability of organisations to anticipate and respond to disruption [19, 23]. According to Taleb [30], organisations that are able to recognise black swans are not fooled by randomness; they have processes and structures in place that are capable of dealing with ambiguity and uncertainty [7, 8] and are able to leverage opportunities to remain competitive [31]. Hence, disruption and opportunities that may flow from the occurrence of black swans are not impossible to predict [19]. In Hitt and Ireland’s

[32] view, recognising black swans is a matter of knowing where to look, having flexible processes in place, cultivating an entrepreneurial mindset and acting swiftly [33].

Recent research indicates that data can also assist in identifying black swans [11, 12]. In many organisations, the role of data has become increasingly important [34, 35] in detecting and understanding environmental ambiguity and uncertainty. Firms that embrace a data-driven approach to decision-making often find that they have to change the design of the organisation [36]. Grossman [37] suggested that data shifts power structures, moving power away from leaders with years of experience to whoever has access to data and the means to analyse them to make strategic decisions [38]. The creation, storage and use of data in high velocity, volume, variety and variability is called 'big data', a term that has only been in use since 2001 [39]. Organisations and consumers already generate large amounts of data, which are predicted to grow exponentially [40]. In their seminal article 'Big Data and Management', George, Hass and Pentland [12] argued that big data change how organisations are designed and managed, their culture and identity and how decisions are made [11, 12]. For many, the most likely path to achieve competitive advantage is via big data analytics [41]. Hence, it is not only newcomers, such as Instagram, Netflix and Amazon, that can benefit from a data-driven approach [42]. Any company can benefit, as big data analytics offer insights by extracting structured information from unstructured data using tools such as descriptive, predictive or prescriptive analytics [43]. In fact, some suggest that big data analytics have become a prerequisite to understanding the business environment and to remaining competitive [44, 45]. Studies show that big data analytics offer organisations competitive advantages [12, 46-48] and that this affects organisational design [36, 46, 49-51]. We argue that, although the role of big data analytics for strategy is important, it is not yet fully understood.

The dynamic capabilities perspective helps to shed light on how to employ big data analytics to detect, anticipate and respond to an uncertain environment. Teece [9] characterised dynamic capabilities as the capacity to sense opportunities and threats, seize opportunities and maintain competitiveness through transforming assets. To understand changes in the environment, he [9, 10] suggested that dynamic capabilities require 'some kind of analytical framework' [9, P1324]. In this study, we seek to further develop the notion of an analytical framework and investigate the role of big data analytics for dynamic capabilities and its micro-foundations, including sensing, seizing and transforming.

We ask: how can organisations apply big data analytics when dealing with ambiguity and uncertainty? We seek to answer this question via a meta-synthesis of 101 academic papers and an analysis of the cases of data analytics therein. The benefits of a meta-synthesis 'can be seen in empirically consolidating primary studies to build theory' [52, P527]. Our method incorporates semantic analytics, NLP and case analysis. This allows us to extract structured information from unstructured data. We then study how organisations use big data analytics to understand their environment and anticipate and respond to ambiguity and uncertainty. Our inductive study has resulted in six propositions that help to identify when various forms of big data analytics can assist with sensing and seizing opportunities and, consequently, transforming different types of organisations. The theoretical contribution of our study lies in the conception of big data analytics as a dynamic capability that supports management in times of ambiguity and uncertainty.

In what follows, we discuss the theoretical background related to black swans, big data analytics and dynamic capabilities. We then propose a conceptual framework and justify our methodology. Finally, we discuss our findings and derive six propositions that depict the key theoretical relationships between big data analytics and dynamic capabilities.

Theoretical background

What are black swans?

The term ‘black swan’ was originally used to connote an extraordinary, unusual or impossible event or phenomenon [53]. After the discovery of actual black swans in their native Australian habitat, its meaning changed, metamorphosing into a perceived impossibility that might be disproven. Taleb [19] used the term to describe events that have a distinct effect on organisations and their environment. However, black swans are not only the result of environmental forces [19]; they are also a consequence of deliberate choices made by management [23]. Choice, chance and environmental circumstances interact in an ever-changing and uncertain world, resulting in positive and negative outcomes for organisations—sometimes in the most unexpected ways. Black swans are events that go unnoticed due to seemingly unconnected nodes in a network and across stakeholders [54] and, as such, imply ambiguity and uncertainty.

Organisations that recognise black swans can create new opportunities and a competitive advantage [31], as it is at the edge of chaos and the unexpected that the greatest opportunities lie [55]. In this instance, predictions are of limited use, as the past is not always the best predictor of the future. This is because of the increasing number of unknown unknowns and their effects [2]. Hence, the strategic challenge is to continuously adapt strategy to a constantly, rapidly and unpredictably changing environment. Such adaptation requires ‘the ability to be open to new evidence and to be nimble and flexible in decision-making’ [3, P2].

Kaisler and Armour [56] have argued that organisations with access to insights from data are more likely to identify black swans. However, the usual methods of statistical analysis, such as regression, correlation or standard deviation, are not sufficient [57]. As well as interpreting signals of a changing environment [33] that may be weak, antennae are required to scan the horizon. Further, organisations require decision-making processes that allow swift action. However, humans are not very good at imagining the unexpected. Managers, like all people, tend to suffer from cognitive biases—that is, they look for what they know (focusing on data that reaffirms beliefs), see patterns in data in which none exist (due to the illusion of understanding), ask the wrong questions (and ignore evidence) and overestimate their knowledge (resulting in tunnel vision) [19, 30].

To detect black swans—to be able to respond to an ambiguous and uncertain environment—organisations must know where to look, be willing to expect the unexpected and act quickly and decisively [33]. Current research indicates that data-driven organisations are in a strong position to deal with environmental ambiguity and uncertainty when they have empowered, connected and decentralised decision-makers [36, 58], and when they have a flexible organisational design and the technological capabilities to innovate across time and space [59]. Research has led to better understandings of what constitutes black swans and how uncertain environments affect organisations; however, there is little research to explain how organisations can successfully respond to black swans.

The role of big data analytics for business

Big data relates to data that are high in volume, velocity and variety [39]. Recently, technologies have been developed to analyse such data (i.e., big data analytics) and these are now used to inform decision-making. When explaining the effect of big data analytics on organisations, authors have pointed to three different types (or stages) of data analytical practices [36, 38, 49, 60-63]: descriptive analytics, predictive analytics and prescriptive analytics [43, 56, 64-67]. Each stage offers insights that can improve and optimise performance and sustain competitive advantage [68-74]. Each stage increases in complexity, as does the value it may add to the business that employs it.

Descriptive analytics enable organisations to learn, filter, shape and calibrate opportunities by providing insights into what has happened in their internal and external environment [75, 76]. Similar to when you look into the rear-view mirror of your car, descriptive analytics looks into the past using multiple structured data sources and statistical methods to obtain insights about what has happened, from a second ago to decades ago [77]. As such, descriptive analytics only offers insights into what has previously happened; it does not provide recommendations on what to do moving forward.

Predictive analytics improves decision-making across the organisation [66]. It is about the future and predicting what will happen [77]; it is like your car's navigation system, directing you to the fastest route around a traffic jam. Predictive analytics uses machine learning and algorithms to find patterns and capture relationships in multiple (un)structured data sources to create foresight [78]. There is an assumption that organisations that use predictive analytics gain competitive advantage because they can anticipate the future [79]; however, insufficient data and flaws or biases in algorithms may significantly harm organisations and their customers [80].

Prescriptive analytics transform organisations. The final stage in understanding a business [81], prescriptive analytics offer recommendations on how to act upon, and take advantage of, predictions. It uses a variety of algorithms and data modelling techniques to gain a thorough understanding of the environment and improve business performance [65]. Likened to a car, it is a self-driving, autonomous vehicle that can pick you up and take you to your destination.

Berner et al. [37, 38] argued that the application of analytics affects the power balance within organisations. Traditionally, the power to make strategic decisions lies with the person who has the most experience, decision-making rights [82] and access to resources or information not available anywhere else in the organisation [83]. According to Bacon [84], knowledge is a form of power that can be gained from power [85]. However, when data and information are widely accessible in real-time, the power balance shifts [37] away from executives who may have years of experience. Thus, when organisations provide more people with access to knowledge through big data analytics, power is distributed more equally, empowering the organisation [36, 38, 86, 87]. Malone [58] observed that balancing top-down control with bottom-up empowerment is increasingly important. Due to the decreasing costs of information technology, decision-making is becoming decentralised. Decentralised organisations are better positioned to benefit from big data analytics [36], as real-time insights enable anyone, not only executives, to make decisions rapidly, resulting in more agile companies [12, 36, 38, 49, 60].

Researchers largely agree on what big data analytics is and how it affects decision-making and power dynamics within organisations. However, we do not know how big data analytics can be employed strategically to understand the environment. Nor do we understand how it can guide strategic choices or affect change for organisations that are facing ambiguity and uncertainty.

Dynamic capabilities as a theoretical lens

Teece and Pisano [88] described dynamic capabilities as those capabilities that enable organisations to develop new products and services in changing market circumstances to gain competitive advantages [89-91]. According to Teece [9], they are most relevant for organisations operating in international and open markets that experience rapid technological change. Dynamic capabilities enable firms to incorporate, build and adjust internal or external assets; they are heterogeneous across firms, enabling highly adaptive behaviour [92] and the agility to manage deep uncertainty [7, 93]. Zollo and Winter [94] found a direct link between dynamic capabilities and superior performance in changing environments.

When seeking competitive advantage, dynamic capabilities offer a deeper understanding of how and when the market and environment are changing [9], which can give an organisation the ability to transform accordingly. Dynamic capabilities must be integrated, developed or reconfigured depending on how circumstances change [95, 96]. Such capabilities emerge by learning from mistakes, practise and experience [89, 97]. Teece [9] considered dynamic capabilities particularly relevant for organisations that are receptive to market and technological developments [95], especially within fast-moving environments that involve global markets and competition. Following on from this, Cavalcante and Kesting [98] have argued that organisations require a dynamic business model to continue operating their existing activities and flexible characteristics to adapt to a changing environment. When faced with industry disruption, a company that has dynamic capabilities is on the lookout for unknown unknowns, while an organisation that applies big data analytics to enhance its dynamic capabilities can create additional value [99-103].

Dynamic capabilities and, in particular, its micro-foundations, focus on how an organisation remains competitive in times of uncertainty [9, 104]. Zollo and Winter [94] argued that micro-foundations are integral to a business model and to the competitiveness of the firm. Teece [9] too notes dynamic capabilities as those capabilities that sense and seize opportunities and, subsequently, transform and realign the assets of an organisation. Sensing is the ability to understand customers, market trends and technological changes; understand the constraints that affect such changes (including laws and ethics); and scan the environment for change [105]. Organisations with dynamic capabilities align internal processes and routines (such as product development), decision-making and culture to seize the opportunities that have been sensed [106, 107]. They do this by determining what technologies to use, business models to apply and market segments to target [9]. Once an opportunity is seized and the strategic direction has changed, the organisation transforms [108]. According to Teece [9] and Wang and Ahmed [109], sensing, seizing and transforming are essential for sustaining profitable growth. The routines, skills and capabilities underpinning sensing, seizing and transforming combine to give organisations a competitive edge in uncertain and changing environments [9]. In addition, Erevelles, Fukawa [102], and Opresnik and Taisch [110] claimed that a big data strategy underpins and facilitates dynamic capabilities to respond to changes in a dynamic environment. Hence, in this study, we apply a dynamic capabilities perspective to better understand how organisations can use big data analytics in ambiguous and uncertain times.

Big data analytics has the potential to enable organisations to better understand the business environment and improve their strategic decision-making. However, we do not yet know enough about what types of data analytics are best suited to achieving such outcomes. In what follows, we propose a theoretical framework based on the dynamic capabilities perspective that links different applications of big data analytics to an organisation's ability to detect and respond to black swans.

Theoretical framework

Following Teece's view that 'some kind of analytical framework' [9, P1324] helps with understanding an uncertain environment, and with the aforementioned theoretical considerations in mind, we argue that different applications of big data analytics can be interpreted using a dynamic capabilities perspective. Data analytics, when conceptualised as dynamic capabilities, can help to interpret the business environment, enable managers to act and result in sustained superior performance and competitive advantage. Therefore, in this study, we investigate the role of descriptive analytics, predictive analytics and prescriptive analytics within organisations in times of uncertainty and ambiguity. We aim to understand how these types of business analytics are linked to dynamic capabilities in general, and the micro-foundations of sensing, seizing and transforming in particular. This leads to our conceptual framework as shown in Figure 1.

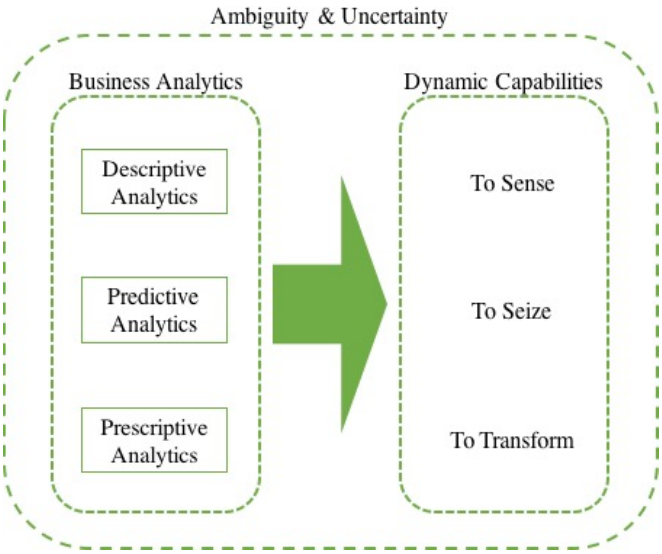

Figure 1: Conceptual framework

Methodology

We carried out a meta-synthesis of 101 peer reviewed academic articles featuring case studies of how organisations have applied various types of data analytics. A meta-synthesis analysis allowed us to draw comparisons and conclusions from these studies [111] by extracting structured information from unstructured data. With the objective of understanding how big data analytics enables organisations to sense, seize or transform to remain competitive, we applied a systematic selection procedure using a semantic data processing approach. The objective of this approach was to use big data analytics to answer our research question. We applied NLP and semantic analytics to the selected papers. This enabled us to extract structured information from unstructured data to understand the concepts within the papers and find patterns among these concepts, thereby exposing the value of using big data analytics tools. In what follows, we explain how a sample of 101 peer reviewed articles was selected, justify the method of analysis (particularly regarding semantic analytics and NLP) and describe how we extracted structured data from the sample for further analysis.

Data gathering process

To arrive at the sample of 101 academic articles covering case studies of data analytics, we began with a search query in leading journals, as recommended by Webster and Watson [112]. We conducted a search using the term 'big data' within 47 A*- and A-rated business and management journals (based on the 2013 ABDC Journal Quality List, the Harzing Quality List and SCImago Journal Rank Indicator) using Web of Science. While Web of Science did not include all articles on big data, it offered further details, including citation analysis [113]. The initial search query returned 45 articles, of which only 27 were deemed useful based on an analysis of abstracts. Next, covering all English academic business journals, we conducted a search using Business Source Complete (EBSCO), again using the term 'big data'. This query returned 9540 results. We refined these results by extending the search query with additional terms selected after discussion with experts in the field. These additional keywords included 'case study', 'example', 'business intelligence' and 'decision-making'. Based on the three levels of big data analytics, we included the terms 'descriptive analytics', 'predictive analytics' and 'prescriptive analytics'. We performed multiple queries, combining search terms in different variations, resulting in 2308 results. The relevance of these articles, in being a business use case of big data, was assessed by reviewing their titles using the keywords. This reduced the sample to 269. Keyword filtering is a useful approach when search queries return such a high list of results [114]. As such, papers focusing on, for example, discussions of technical big data implementations [115, 116] were excluded.

Method of analysis

We used semantic analysis and NLP to discover topics within the papers to further reduce the sample. This approach was appropriate as it enabled us to understand how different topics were correlated. Further, information extraction using semantics and NLP enabled large amounts of text to be synthesised to provide detailed conceptual insights [117, 118]. This method has been applied across a wide range of research [119-121], including business [122, 123], but predominantly in health and biomedical research [124-126], and has been instrumental in analysing extensive health documents to discover new scientific results. Information extraction entails automatically extracting structured information from unstructured data, usually through NLP, to discover semantic relations between concepts of interest [117, 121, 123, 127, 128]. Once extracted, the information can be used to develop a graph that shows the relationship between multiple concepts [119]. The processing of the articles and extraction of computer-generated abstracts consisted of three steps.

(1) *Pre-processing*: the first step focused on the case study only; we did not include literature reviews as these could contaminate the data. Therefore, we extracted the text and publication structure from the PDFs to exclude the literature reviews of each academic paper.

(2) *Topic models*: the second step consisted of automatically discovering important phrases using topic models and collocations - two words that habitually appear together and convey a certain meaning [129] - called Latent Dirichlet Allocation (LDA) [130]. LDA is a statistical model used to decide on the topic of a previously unseen document. This is based on determining the probability a topic has of generating a particular word. We continuously updated that probability by continuously analysing the document [130]. We used a standard topic modelling tool: the MALLET topic model package [131, 132]. Subsequently, we expanded this list

using Wordnet, which is an NLP resource consisting of a hand coded lexical database for the English language [133].

The purpose of applying topic models is extracting terminology from the document collection and organising it in the form of lexicons [134]. Using pre-approved lexicons allows to easily see the cause of the system results, as well as improving it. Manual creation of lexicons imposes prohibitive costs and calls for automated tools. Topic models allow grouping similar words together, for example, to put industry terms into one topic. While the method is unsupervised, and the results require human review, it is still a substantial reduction of manual work comparing to skimming through the documents.

(3) *Extraction of words and phrases:* the third step involved extracting important words and phrases from the sample and linking them to the different categories we had defined. For example, we extracted change indicators ('reduce', 'improvement', 'benefit'), business processes ('decision-making', 'customer understanding', 'customer relation management') and company properties ('size', 'revenue', 'country', 'industry'). This step turned unstructured text into structured text and enabled us to gain relevant insights.

Categorisation

Aside from the automatic generation of abstracts, we applied a rule-based approach in our analysis to classify several variables. This enabled us to avoid false hits from the information extraction [135]. Text categorisation entails assigning extracted text to one or more predefined categories to understand relationships between different concepts [136]. To provide insight into the effect of big data analytics among organisations, we defined four categories.

1) *Type of organisation*: we defined four types of organisations most relevant to dynamic capabilities [137-139]. These were small and medium enterprises (SMEs), large corporates or multinational enterprises (MNEs), government organisations and not-for-profit organisations.
2) *Industries*: we chose to use the Industry Classification Benchmark (ICB) to classify different industries. The ICB is used globally and consists of 10 industries, subdivided into 19 super sectors. These super sectors are further partitioned into 41 sectors, which are comprised of 114 sub-sectors. This subdivision enabled us to connect the variety of sectors in the sample to 15 main industries. We extended the list with several classifications such as government, education and not-for-profit. These have not been included in this list since it was launched by the Dow Jones and FTSE.
3) *Level of big data analytics*: we outlined descriptive, predictive or prescriptive analytics, as discussed earlier.
4) *Type of application, or use case, of big data analytics*: the micro-foundation sensing, seizing or transforming, that is pursued by the organisation discussed.

In addition, we incorporated the impact of the journal that published the article. We used the 2015 SCImago Journal Rank as it uses a larger source journal database (covering 29,713 journals) than the Journal Impact Factor, and focuses on quality, rather than quantity, of citations [140].

This analysis resulted in the creation of an excel document with a computer-generated summary of each article that contained structured information such as title, journal name and year of publication, as well as industry and country, if available. However, industry and country were too unreliable to use and we were forced to extract this information manually.

We read and analysed the computer-generated abstracts of the 269 papers to determine their relevance to this study. We excluded papers that did not feature a case study analysis. For example, articles focusing on the penetration of business intelligence systems [141], new approaches to data extraction [142] or the development of a methodological framework for retail forecasting [143], were excluded. If the computer-generated abstract was not sufficiently comprehensive, we read the original abstract of the paper. We only selected articles that featured a case study because these provided insights into existing or past events within a constantly changing context [144, 145]. The case study methodology is especially appropriate in new topic areas [146] and is the best way to understand a certain phenomenon over time [145, 147].

This resulted in a final sample of 101 articles that featured relevant case studies of big data analytics. Each article discussed an application of big data analytics within an organisation. Table 1 provides an overview of the selected articles. The articles discuss a variety of cases from different contexts. This enabled us to synthesise qualitative case studies [52] and understand different applications of big data analytics across different contexts. As Hoon [52, P523] has observed, such a meta-synthesis is considered inductive as it aims to make 'contributions beyond those achieved in the original studies'. We believe that our systematic selection process produced a sufficiently large sample to be demonstrative in respect of the existing research on big data analytics. Figure 2 shows a graphic overview of the papers included in this study based on their impact factor and dates of publication. This demonstrates that big data papers have only begun to appear in recent years. This makes sense, as big data analytics have only been adopted by organisations in the last decade:

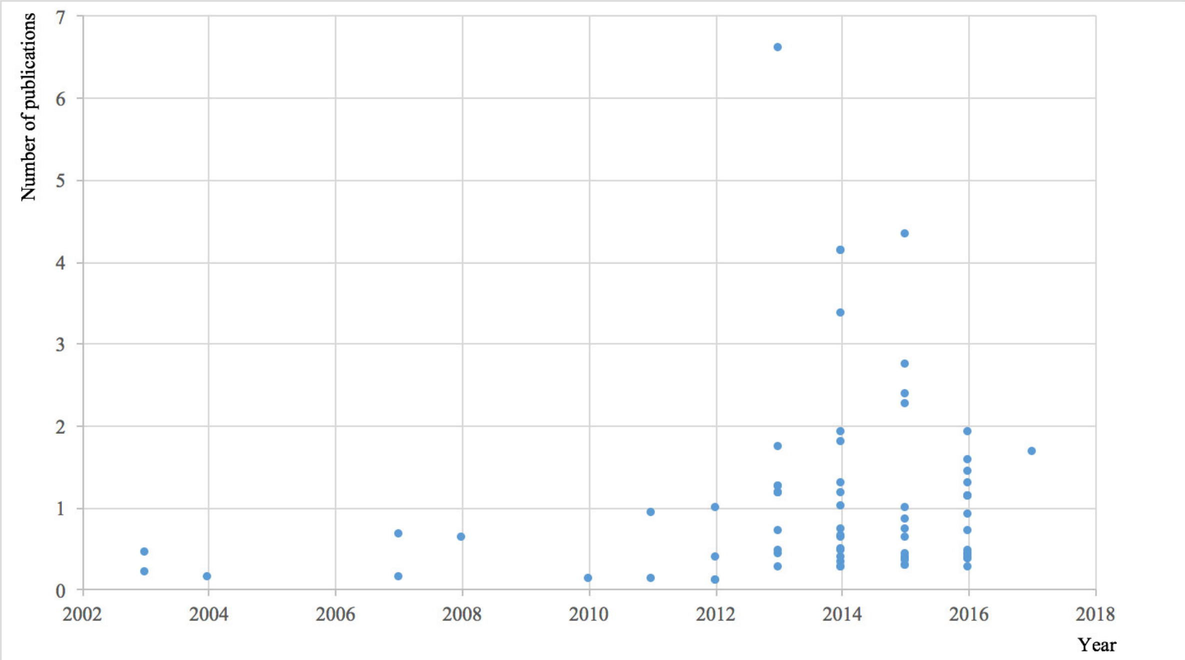

Figure 2: Overview impact factor and publication date articles used

Extracting structured information

We applied further semantic analysis on the remaining 101 papers to extract semantic relations and the lexical/structural context of the level of analytics used, as well as the type of use cases described within the case studies. Semantic relations determine word definitions [133]. Understanding the lexical and structural context of words and phrases was thought to automatically determine the use case as well as the application of big data analytics. However, this was more challenging than we anticipated. We applied NLP to determine the four abovementioned categories for each case study. Each category required allocation of a specific value (e.g., country or year) or a text fragment that makes sense to human annotators. However, the complexity of the fields varied in two dimensions: how well the field can be defined (i.e., human agreement on annotations) and how various vocabulary and grammatical structures appear around the field values in the publication. This directly influenced the accuracy of the algorithm. For example, ‘year of publication’ had higher accuracy, while accuracy for ‘analytics type’ and ‘use case’ was much lower. As such, we decided to manually code all 101 articles to determine the types of analytics, use case and, in some cases, industry and country of the organisation described in each case study. This was achieved by reading all 101 articles and using expert knowledge to code the correct category for the different fields. We analysed each individual case according to the four categories specified. This coding system helped us to understand the particular structure and configuration of the variables that characterised each study [148]. We coded specific words that would indicate either sensing, seizing or transforming. For example, to be able to detect sensing we searched for words that suggested obtaining an understanding of customer and market trends. We looked for terms such as ‘customers’, ‘suppliers’, ‘target market’, ‘needs’, ‘technologies’, ‘churn’, ‘360 degrees’ and ‘personalisation’. In regard to seizing, we searched for concepts related to improving organisational processes and managerial activities. We coded terms such as ‘decision-making’, ‘business processes’, ‘leadership’, ‘improving’, ‘improvements’ and ‘culture’. Finally, to identify transforming we searched for concepts linked to (co)creating and innovating new products and services. We coded words such as ‘innovation’, ‘product development’, ‘create’, ‘services’ and ‘value’. As suggested by Hoon [52], our objective was to merge the different case specifics using our theoretical framework, understand patterns among the different case studies and contexts [149], and translate the different concepts and categories from one study to another [150, 151], thereby deriving our six propositions. We included insights and quotations from a selection of articles in our results section to emphasise the characteristics of the different case studies, how they linked to other case studies and to provide more context on the articles included in our research.

Sample characteristics

It should be noted that all case studies were recent (see Figure 2), which is not surprising given that 'big data' has only been around since 2001 [39]. Figure 2 shows that most of the case studies appeared in journals of low rank, since the initial search resulted in few A- or A*-ranked journal articles.

As with some of the characteristics of the companies researched, Figure 3 shows that the geographical distribution was wide. Most companies we analysed were in the United States (US). This is not surprising. According to market research, the US is at the forefront of organisations applying big data analytics [152]. Figure 4 shows the different industries, based on the extended ICB industry list. The predominant industries that have been researched are consumer services, financial services, government, media and consumer goods. In some ways, this is in line with market research, indicating that the top industries investing in big data are banking (financial services), manufacturing (industrial) and government [153]. Overall, we are confident that although the data set is relatively small, it covers a relevant sample.

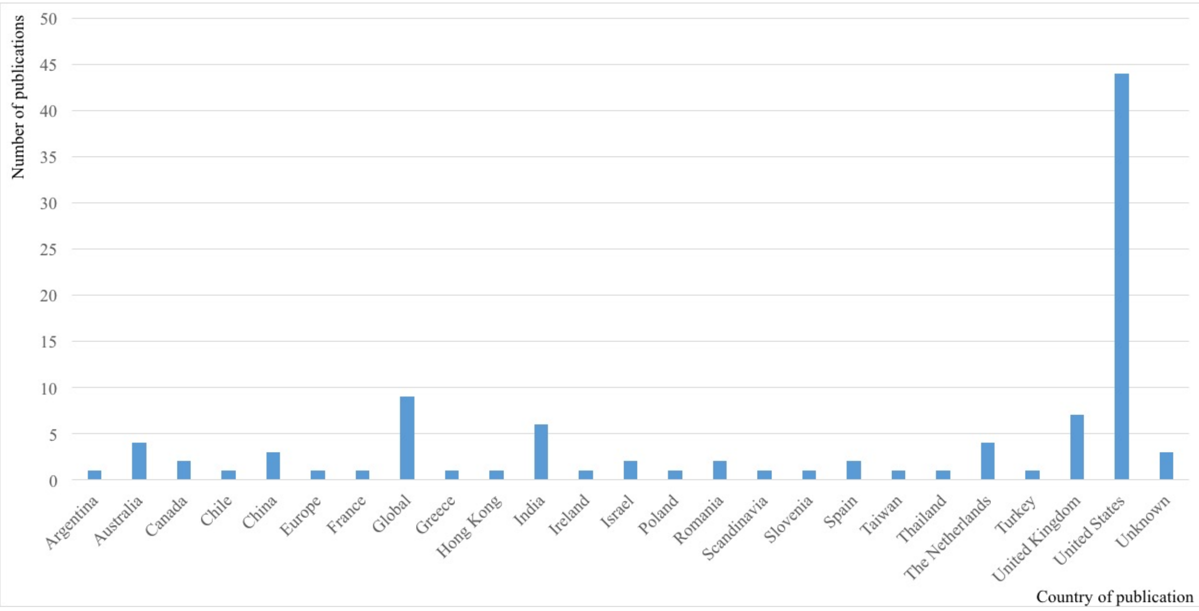

Figure 3: Origin of companies in case studies

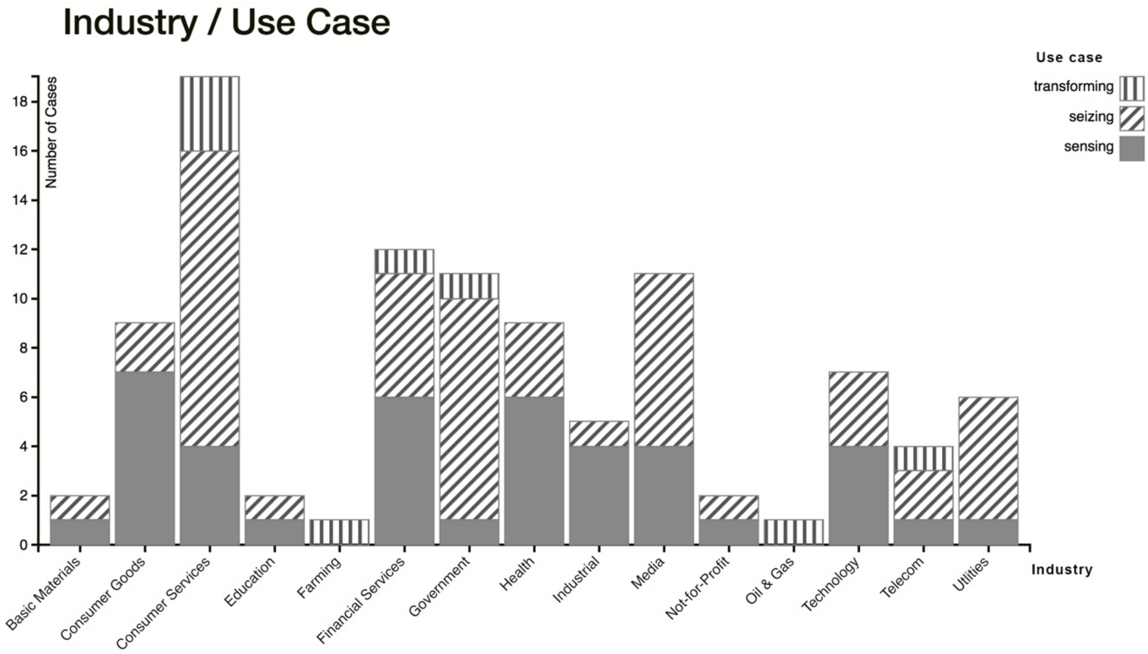

Figure 4: Industries vs use case

Dimension	Descriptive analytics	Predictive analytics	Prescriptive analytics
Sensing	[70, 154-187]	[69, 188-203]	[81]
Seizing	[204-219]	[46, 220-240]	[241]
Transforming		[36, 48, 68, 242-246]	

Table 1: 101 use case articles analysed for meta-synthesis

Results

In total, 101 case studies were analysed. Although some case studies discussed multiple companies [156, 167, 169, 171, 179], the authors of these articles analysed the social media activities of multiple companies as evidence of how social media (descriptive) analytics had been used to understand customer behaviour (sensing). Therefore, we looked at each article as representing one case study. In addition, we chose to code only one variable of each category for each case study. We did this to prevent skewed results in which the same case study would appear twice in the results. In what follows, we discuss some of the structured information we discovered in the articles and use these insights to develop multiple propositions related to descriptive, predictive and prescriptive analytics. We also discuss some additional findings.

Use case vs. type of analytics

Descriptive analytics

Our research revealed that many organisations applying big data analytics use descriptive analytics. As Figure 5 shows, 52 companies applied descriptive analytics within their organisation. Of these, the majority, 35 organisations, did so to sense their environment and understand customer needs and their changing environment. Teece [9] defined sensing as those activities that scan, search and explore across markets, technologies and customers to understand latent customer needs, technological progress, the evolution of markets and potential responses from suppliers and competitors. Discovering opportunities requires access to structured information [9, 247]. The micro-foundations Teece [9] identified as part of the framework for sensing include elements such as research and development activities to find new technologies and processes. These identify supplier innovation, new markets and changing customer needs and should be embedded in the organisation [9], as they help to understand its context [91]. The 35 organisations applied descriptive analytics to sense their environment in a variety of ways.

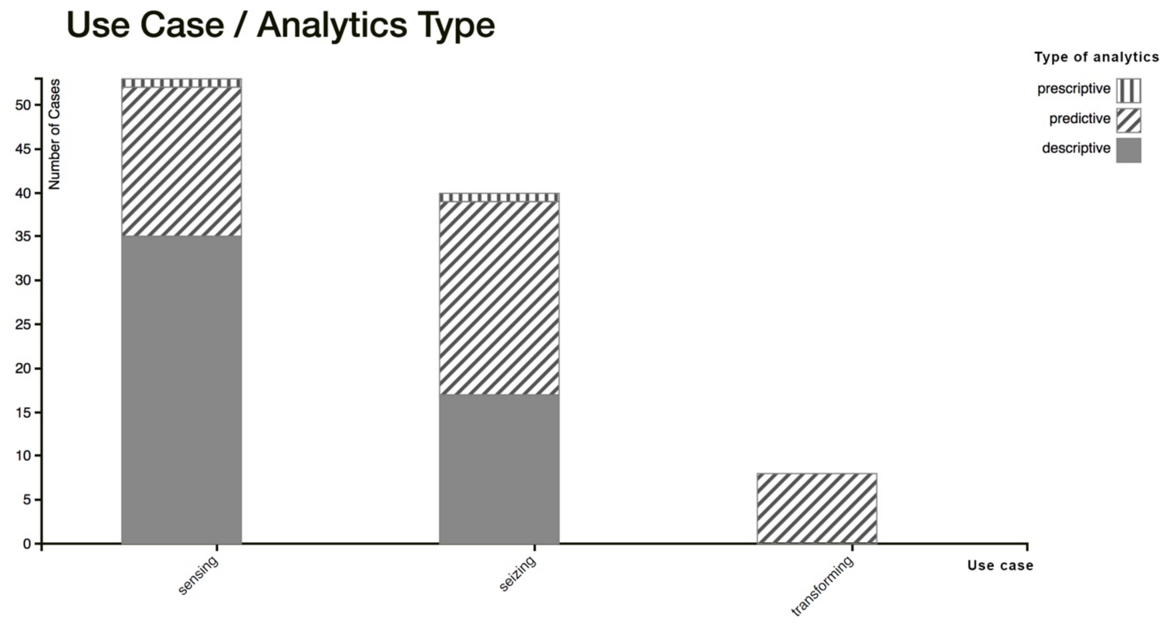

Figure 5: Use case vs analytics type

For example, using the business intelligence software Qlikview, a Dutch mortgage advisory company with 100 shops applied mobile descriptive analytics to offer insights into consumer behaviour and market conditions [175]. As the authors, Verkooij and Spruit [175, P29], commented, this 'solution integrates six internal as well as external data sources to provide these business insights' and offered shop managers an iPad to view insights anywhere, anytime. The city of Boston applied mobile descriptive analytics to facilitate road infrastructure management. As O'Leary [168, P181] explained, the city developed an app called Street Bump that 'uses the mobile phone's accelerometer to detect potential potholes. It uses the phone's global positioning system capabilities to gather location information of that pothole.' The citizen-generated sensor data offered insights into road conditions and enabled the government to identify areas of improvement. Both are examples of what Teece [9] and Nonaka and Toyama [247] described as having access to information to discover opportunities. In addition, as Helfat and Peteraf [105] argued, descriptive analytics enables organisations to scan the environment for change, offering a better understanding of the context of the organisation [9].

Apart from context, understanding change among stakeholders is key [91]. A joint venture in the United Kingdom between three magazine publishing companies [165] used descriptive analytics to monitor different actors within the magazine's distribution supply chain. The joint venture embedded descriptive analytics within the supply chain to analyse various structured data sources from multiple suppliers and wholesalers, which as noted by Teece [9], enables organisations to examine key performance indicators (KPIs) and supplier processes [165].

Zollo and Winter [94] are in favour of making analytics capability an integral part of the business model, which is what Nielsen did to understand consumer behaviour [70]. Nielsen, 'the ratings engine for the advertising industry' [70, P574], offered information to its customers regarding the viewing and purchasing behaviour of consumers. The company collects billions of records and uses advanced technology (such as neuroscience) to further its objective of measuring viewer attention and involvement when exposed to advertising [70]. As Kaisler and Armour [56] argued, this offers stakeholders insights in a changing environment.

Finally, the city of Barcelona analysed user-generated content to understand tourist profiles [182]. An analysis of 100,000 travel blogs and reviews written by tourists who had visited Barcelona gave the city insights into its 'customer' and produced detailed profiles of visitors [182]. The city employed descriptive analytics to obtain insights on changing tourism behaviour to identify new markets and customer trends [9].

As these case studies show, descriptive analytics is used to understand the environment and to discover patterns in customer behaviour or market trends. It helps organisations detect opportunities in times of ambiguity and uncertainty, as data on customer and market trends provide insights and clues into the changing environment of an organisation [56]. Therefore, descriptive analytics offers the antennae required to detect the weak signals that indicate a changing environment [33, 91, 105] and changing customer behaviour [9]. Descriptive analytics helps to understand the environment of an organisation by providing insights related to the past [9]. We summarise this with our first proposition:

Proposition 1: Descriptive analytics enable organisations to better sense opportunities in times of uncertainty.

However, descriptive analytics is not only applied to sense the environment. It also appears that, in some (17) case studies, it can be related to improving internal processes in response to changing environments—that is, seizing. For example, a subsidiary in the US of a multinational financial services firm used detailed customer profiles to manage its customers. The company needed this information to 'make actionable and potentially business-altering decisions' [209, P329]. Descriptive analytics was used to segment customer data, integrate these with external data and build a customer cross-sell platform [209]. As observed by Kindström and Kowalkowski [106], such activities help to better seize opportunities that appear from insights.

Another example is the international fashion retailer, GUESS? Inc, which applied descriptive analytics to improve its decision-making capabilities and drive business actions [214]. The global retailer used a mobile analytics platform, GMobile, to turn fashion trends and customer data into insights that allowed buyers, planners and distributors to place 'the right apparel in the right store at the right time to appeal to its fashion-savvy shoppers' [214, P114]. Using mobile business intelligence, GMobile offered access to information [9, 247] and visually displayed information, such as bestsellers or sales information, enabling employees to know what markets to target [9].

The St. Joseph Mercy Oakland Hospital applied descriptive analytics to improve internal processes and managerial activities, such as the hospital's leadership. It did not use a mobile application; instead, the hospital used digital dashboards showing KPIs in prominent locations to improve operational processes and health management programs and initiatives [212]. As well as providing access to information, as argued by Nonaka and Toyama [247], the dashboards helped to mitigate risks and allow users to 'adapt to changes in the organisational culture' [212, P328]. According to Chesbrough [107] and Kindström and Kowalkowski [106], such practices foster innovation, resulting in better internal processes.

Finally, a Thai coal-fired power plant employed descriptive analytics [219] to create insights from data generated through emission monitoring platforms to reduce NOx emissions and comply with air pollutant emissions. It did this by collecting multiple petabytes of data from multiple structured sources to improve operational decision-making, which, as Kindström, Kowalkowski [106] and Kay [248] argued, allowed them to 'improve the performance of the power plant' [219, P1797].

These case studies demonstrate that descriptive analytics is also used to improve organisational processes and decision-making capabilities, enabling an organisation to seize opportunities [9, 106, 107]. We encapsulate this in our second proposition:

Proposition 2: Descriptive analytics help organisations to improve internal processes to respond to a changing environment.

Predictive analytics

Once customer and market trends are understood, a business prepares to seize those opportunities [9]. This requires decision-making in circumstances of uncertainty and 'investments in development and commercialisation activity' [9, P1326] to ensure the correct structures, procedures, designs and incentives are in place [9]. Teece [9] identified that, among other factors, this process involved selecting decision-making protocols [248], designing product and revenue architectures, and improving processes and managerial activities such as leadership, communication and organisational culture. In short, it meant preparing the organisation for seizing opportunities previously sensed, based on insights and creativity as well as stakeholder intelligence [9]. These activities anticipate detected unknown unknowns and prepare potential responses. Predictive analytics offers predictions to improve decision-making processes and to understand what opportunities should be seized.

As Figure 5 shows, we identified 47 organisations that applied predictive analytics within their businesses and 22 that used it to seize opportunities. These organisations applied predictive analytics to improve decision-making protocols, improve processes and develop the organisational culture to seize sensed opportunities. As the case study on Netflix shows, predictive analytics was applied in the use of detailed customer information to 'improve members' retention, reduce cancellations, achieve long-term fidelity, and obtain positive satisfaction ratings for their product' [240, P571]. In addition, Netflix applied predictive analytics, which, as claimed by Kay [248] and Kindström, Kowalkowski [106], allows for offering product recommendations and facilitating customers' decision-making, on, in Netflix's case, what to watch [240]. In this way, through the analysis of vast troves of data, Netflix is able to seize opportunities based on its deep understanding of its customers' preferences.

The case of the Indian industrial company Ramco Cements Limited (RCL) shows how operational data and Enterprise Resource Planning data analyses enable 'more intelligent business decisions' [227, P298]. RCL used extensive data visualisation techniques and predictive capabilities to analyse multiple complex data sources, analysing the geo data of trucks, plant data and customer data to optimise processes and improve decision-making [227]. The predictive capabilities that RCL implemented can be linked to dynamic capabilities, since predictive analytics enables an organisation to improve its processes [106], make better decisions [248] and respond to changes in their environment [9].

The case of a large financial institution with more than 8,000,000 customers in 10 countries shows that social media analytics can be used to understand customer profiles [9] and 'to enable informed and insightful decision-making' [239, P3728]. The bank applied sentiment analysis on social media activities to source potential new customers, gaining insights that were integrated into outbound marketing campaigns to attract new customers. In addition, predictive analytics enabled the organisation to cross-sell and upsell products to customers based on certain lifetime events [239]. As such, the bank grew its analytical capabilities, which Makadok [97] and Teece [9] argue enables and organisation to make better decisions in circumstances of uncertainty.

Finally, we have the case of a global media conglomerate applying predictive analytics to improve inventory management, which, as argued by Chesbrough [107] and Kindström, Kowalkowski [106], prepares internal processes for a changing environment. The firm in question, one of the largest distributors of multimedia, used internal transactional records, public data and Google search data to optimise inventory management [234]. Predictive analytics enables the firm to have the correct inventory at the ideal location, depending on customer demand.

These and other cases among the 22 identified in our research, demonstrate that organisations actively use predictive analytics to seize opportunities by optimising processes and improving their decision-making capabilities. As such, we make a third proposition:

Proposition 3: Predictive analytics enables organisations to seize opportunities by optimising processes and improving decision-making capabilities.

In 17 cases, predictive analytics was applied to sense opportunities and understand customer needs, market trends and competitors' actions. For example, an analysis of written customer reviews from an online review website, Reviewcentre.com, demonstrates that predictive analytics can extract recommendations on customer satisfaction and predict their effect on company performance [189]. As such, predictive analytics can be used to understand customer behaviour [9] and the effect on the business.

In another example, a Chinese bank was described as generating 'insights for active customers based on their transaction behaviour, using close to 20 terabytes of data' [194, P1]. The data enabled the bank to identify online customer behaviour; predictive analytics offered insights into customers who were likely to drop off and those who were actively using online services. The bank went beyond 'traditional customer analytics … using unstructured data that has not been used before' [194, P8], which as Helfat and Peteraf [105] argue, allows for understanding changing customer behaviour. The next step would be to turn those insights into business rules to improve decision-making [248].

Finally, a case study of the Samsung Galaxy i9300 shows that analysing customer reviews using predictive analytics can offer insights into future customer demands [198]. The case study suggested that the 'designers of i9300 are recommended to consider how to improve the performance of battery and provide a larger memory space to consumers' [198, P3033].

Therefore, organisations not only use descriptive analytics to sense opportunities; they also turn to predictive analytics to understand their environment [91]. As such, we suggest a fourth proposition:

Proposition 4: Predictive analytics offers insights into consumer behaviour, as well as changing market demand.

Prescriptive analytics

Sensing and seizing opportunities, or detecting and anticipating unknown unknowns, prepares an organisation for profitable growth and competitive advantage to help avoid unfavourable outcomes [9, 94]. However, the key to sustained competitive advantage is the capability to change routines and develop new products and services depending on changing market circumstances [9, 88]—that is, to respond to unknown unknowns [31]. According to Teece [9], this requires a continuous (re)alignment of assets and includes elements that are involved in embracing innovation [249] and decentralisation, thereby ensuring value-enhancing product development or knowledge management skills that respond to disruptive innovation [250]. The objective is to (co)create and innovate new products, services and business models that match the sensed and seized opportunities. As observed earlier, prescriptive analytics can offer recommendations on how to act upon predictions to take advantage of seized opportunities and, potentially, (re)align assets to transform businesses. However, our research revealed that organisations do not apply prescriptive analytics to transform their business or (re)align their assets. This may be because prescriptive analytics is a nascent technology that is applied only by few organisations (e.g., Facebook and Google). Market research showed that worldwide revenue of big data was $122 billion in 2015, with only $415 million generated by prescriptive analytics software [251]. In addition, although prescriptive analytics is likely to offer the greatest benefits for organisations, a lack of available software, data and computational requirements may prevent organisations from applying prescriptive analytics [81]. As Figures 5 and 6 demonstrate, there were only two cases of prescriptive analytics in our research sample; these were used for sensing and seizing by an SME and a government. In these two cases, prescriptive analytics were applied to understand consumer behaviour at a utility organisation [81] and to improve data-driven decision-making at a steel bar products manufacturer in North America [241]. Since evidence of organisations applying prescriptive analytics in our study is weak, we are not comfortable deriving a proposition. However, at the conclusion of this paper, we offer further discussion and suggest a future research agenda regarding prescriptive analytics.

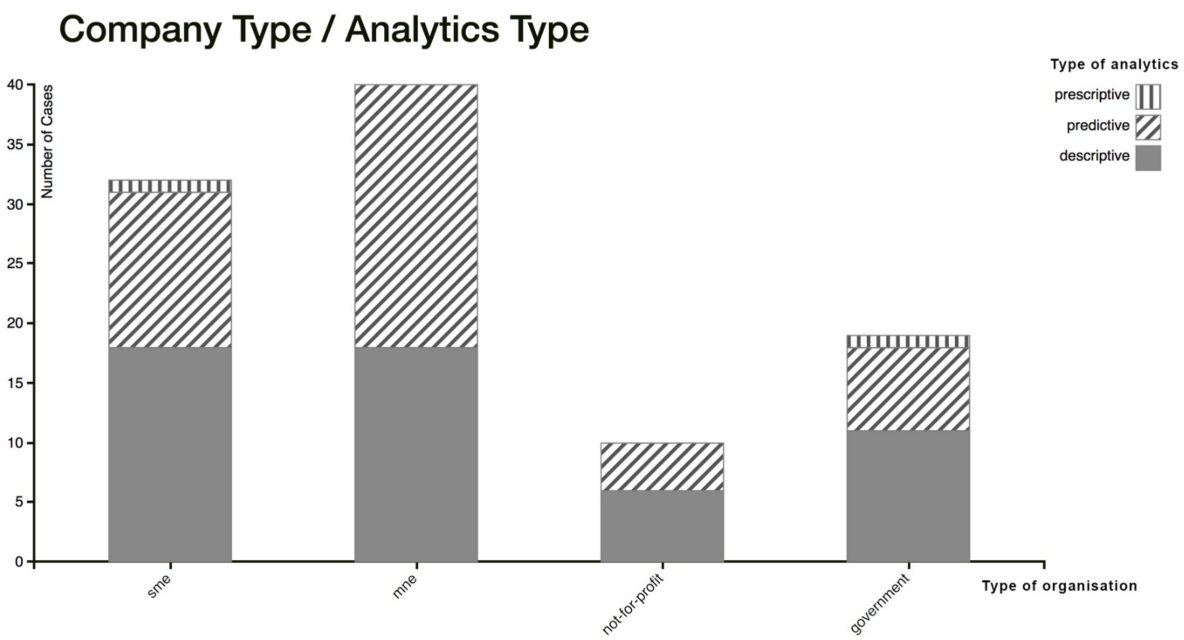

Figure 6: Company type vs analytics type

Figure 7 shows that few organisations apply big data analytics to transform their assets and that SMEs and not-for-profit organisations do not use big data analytics to transform their organisations.

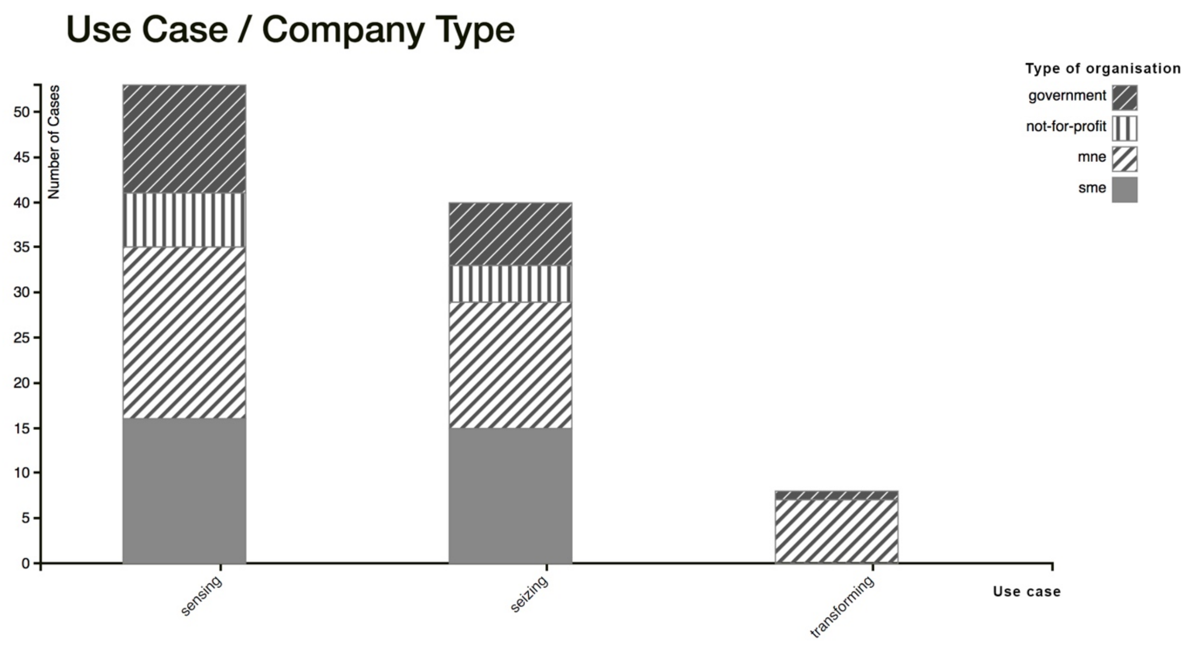

Figure 7: Use case vs company type

As SMEs and not-for-profit organisations generally lag behind in the adoption of big data analytics [252, 253], it is not surprising that they are not using such analytics to transform their organisations. However, eight organisations in our research sample did transform themselves using a form of analytics. Each of these applied predictive analytics to transform their business in one way or another. None used descriptive analytics. This was expected, as descriptive analytics offers insights based on historical data [208, 254-256] that overlooks predictive and prescriptive aspects relevant to transforming an organisation [81].

To transform an organisation, predictive analytics was applied in several ways. A French telecommunications organisation applied predictive analytics ‘to reduce operational cost, increase operational feasibility and enhance cross-sell/upsell opportunities’ [243, P81]. This offered the organisation the flexibility to create new, value-enhancing products, which is vital for sustainable growth [109]. The Bank of England embedded analytics in its policies and actions, which Teece [9] argued is what should be done. It used more than 1000 structured and unstructured data sets to create new, futureproof policies [242]. The city of Amsterdam used predictive analytics to turn itself into a smart city [245]. In doing so, and in line with Snow and Fjeldstad's [257] research, the city collaborated with different commercial and governmental organisations to improve itself, combining data sources to predict traffic flows, make changes (if necessary) and alleviate congestion on the streets [245]. Finally, the car company Ford used predictive analytics—or, as Ford calls it [48, P5], 'pervasive advanced analytics'—to improve the development of cars, resulting in better cars that are produced more efficiently. The telecommunications organisation, the Bank of England, the city of Amsterdam and Ford are examples of organisations applying predictive analytics to transform their assets to anticipate a changing environment [9, 108, 109]. Therefore, while due to lack of available research we cannot offer a proposition on prescriptive analytics, we provide a proposition on how transformation can be achieved with predictive analytics. This leads us to our fifth proposition:

Proposition 5: Organisations can apply predictive analytics to transform their assets to anticipate a changing environment.

Discussion

In this study, we found that both descriptive and predictive analytics enable organisations to sense and seize opportunities in changing environments. These types of analytics allow organisations to turn data into information, thereby offering a competitive advantage [12, 46-48]. As Kaisler and Armour [56] argued, organisations that have access to information are more likely to understand ambiguous and uncertain environments. Although historical data—that is, descriptive analytics—may not be a good predictor for this [2], it does offer insights into the weak signals that can identify a changing environment and may indicate where to look when trying to detect a changing environment [33]. Organisations applying descriptive analytics, or business intelligence, obtain valuable insights that can guide them in their decision-making, whereby decisions are based on the historical context of the environment instead of based on intuition. In addition, as Petrick and Martinelli [3] have argued, if one wants to remain competitive, flexibility in decision-making and flexible organisational processes that can deal with ambiguity and uncertainty [7, 8] are key [31]. Our research suggests that predictive analytics enables organisations to improve their decision-making processes by not only providing the historical context, but also recommending the best course of action to be taken based on the full context of the environment. As such, it can be argued that descriptive and predictive analytics allow organisations to understand ambiguous and uncertain environments and it means that the traditional way of decision-making, based on experience and expertise [258, 259], is exchanged for data-driven decision-making [36]. However, whether information and processes alone are sufficient to respond to such environments is unclear; therefore, additional research is required. Nevertheless, our research suggests that the framework of descriptive and predictive analytics and, potentially, prescriptive analytics, offers the possibility of comprising the analytical framework required for dynamic capabilities, as put forward by Teece [9]. Further, as Snowden and Boone [20] argued, a deep understanding of context is required for leaders who face increasing ambiguity and uncertainty; we suggest that this is possible through big data analytics. Thus, we contribute to the existing literature of dynamic capabilities by supporting and further expanding the notion of an analytical framework as a requirement for the dynamic capabilities framework. In addition, the managerial implications of our research involve an increased understanding of the importance of big data analytics to obtain a better understanding of an organisation's context, which improves an organisation's decision-making and, potentially, results in a competitive advantage.

Our research revealed some additional insights. As shown in Figure 8, the majority of organisations in our study (44 companies) were MNEs that applied big data analytics in different ways for different use cases.

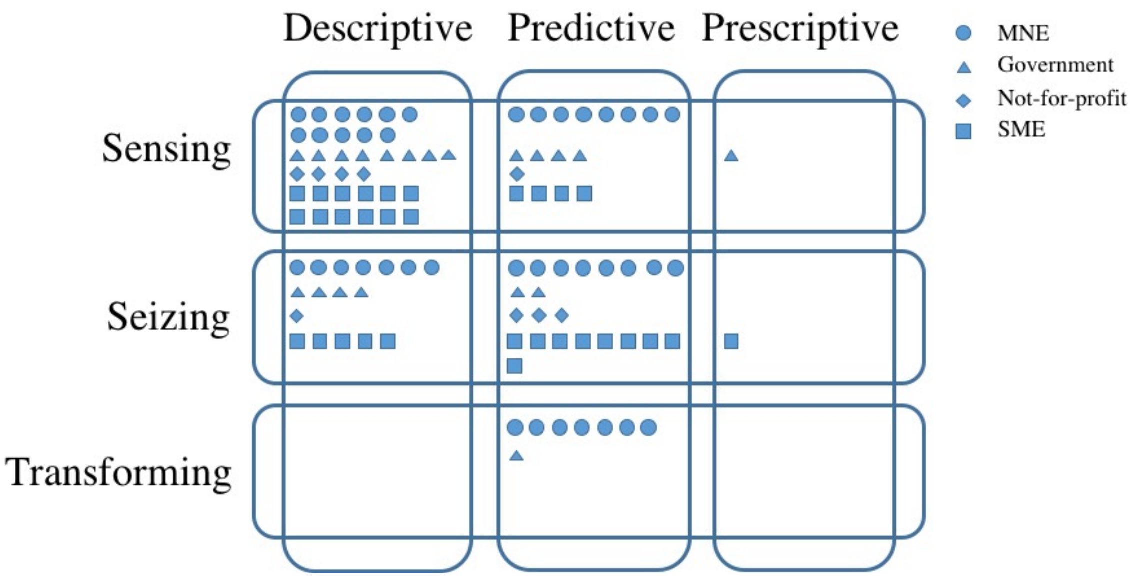

Figure 8: Analytics vs use case vs organisation

Figure 8 shows that MNEs are present in five quadrants. Teece [139] argued that MNEs must amplify their dynamic capabilities. Our research demonstrates that big data analytics can be observed as a dynamic capability that helps to understand the environment, enables managers to take action and provides organisations with sustained superior performance and competitive advantage in times of ambiguity and uncertainty. This is in keeping with earlier studies by Jalonen and Lönnqvist [260] and Galbraith [261].

MNEs have an organisational structure that ensures empowerment and decentralised decision-making capabilities, giving them an additional advantage. MNEs span multiple jurisdictions and territories in which variables such as technologies, infrastructure, markets and customer demands are different. The most common administrative structure for MNEs is a decentralised network organisation [262]. MNEs operate through a network of marketsensitive self-organising business units [263, 264] that are vertically or horizontally integrated [265]. Such geographically dispersed organisations have antennae across time and space that enable them to be receptive to change and to understand how an environment is changing [59, 266]. In addition, regarding knowledge and information sharing, decentralised nodes tend to be open and dynamic across and within different units [267]. These characteristics enable organisations to rapidly and efficiently respond to changing market demands and uncertain environments [264, 268-270], making them adaptable to their environment, receptive to change and flexible in operation [59, 263]. This suggests that MNEs are particularly suited to dealing with deep ambiguity and uncertainty [59]. This leads to our sixth, and final, proposition:

Proposition 6: MNEs are most likely to apply big data analytics in ambiguous and uncertain environments.

This sixth proposition implies that especially managers of MNEs could benefit from generating insights via big data analytics about their changing environment. Hence, leveraging internal and external data sources from across the organisation can help managers of MNEs obtain a clear picture of the context and improve their decision-making capability, which in turn may lead to competitive advantage. Circumstantial evidence from strategic management practice supports our proposition. For example, Pitney Bowes and General Electric (GE) are known to have leveraged data analytics using information produced from Pitney Bowes' shipping machines and customers [271]. With customized asset performance management applications developed by GE, Pitney Bowes was able to offer improved job scheduling capabilities and productivity and client services to its enterprise clients [272]. Another example is PopSugar, a lifestyle media company. PopSugar uses data analytics to produce engaging content that its readers find relevant and valuable. Data analytics enables

PopSupgar to understand the context of audiences and business value drivers. For instance, PopSugar was able to determine from 231,000 social shares and 7 million views that childhood nostalgia and recognizable product names help increase social shares and readership [273], information that the company immediately leveraged in their strategic marketing.

Companies such as Pitney Bowes or PopSugar benefit from better understanding their environment via big data analytics, especially in times of ambiguity and uncertainty. With that, the practice of strategic management changes as organisations move from decisions based on experience and intuition [274] to decisions based on data [11, 12]. The ability to analyse data and understand insights derived from data [61] is increasingly becoming a sought after strategic management skill.

This research contributes to significantly expanding the notion of 'some kind of analytical framework' that Teece [9] refers to as being required for understanding and developing dynamic capabilities. We have clarified what the analytical framework entails in the context of ambiguous and uncertain environments, and our specific contribution to the field lies in the evidence of the value of descriptive and predictive analytics to better understand the fast-changing environment of an organisation and to improve the decision-making capabilities that could result in achieving competitive advantage. As such, the importance of our contribution lies in the understanding that to achieve competitive advantage using dynamic capabilities [9, 10], organisations require an analytical framework consisting of descriptive and predictive analytics. With big data being everywhere and an increased emphasis on data-driven organisations and smart environments [12], our theoretical and practical contribution of seeing big data analytics as a dynamic strategic capability can help organisations, if implemented well, to add value to their business and remain relevant in a fast-changing environment.

Areas for further research

In this study, via six propositions, we developed a conceptual understanding about how big data analytics can be used in ambiguous and uncertain environments to inform strategy making. Furthering our attempt to expand the notion of ‘an analytical framework’ [9], we can now explain, in more detail, how different types of big data analytics relate to strategic dynamic capabilities. The conceptual framework can help scholars and practitioners better understand the notion of the analytical framework; however, it also reveals the need for further research.

While our research suggests that MNEs are most likely to apply big data analytics tools, it has not shown that MNEs are better suited to deal with ambiguity and uncertainty than other types of organisations. This may be explained by the suggestion that researchers had better access to larger, rather than smaller, organisations. Hence, this imbalance among types of organisations might be caused by a lack of research. Further research may be required to gain insight into the types of organisations that are best suited to detect, anticipate and respond to uncertain environments. We suggest that future studies focus on different types of organisations (i.e., MNE v SME v not-for-profit v government) and examine which ones are best suited to benefit from big data analytics.

Figure 8 offers insights into which types of organisations may benefit most from different types of analytics during the stages of sensing, seizing and transforming. However, further research is required to understand which types of analytics work best for different types of organisations during different stages of dynamic capability deployment. For example, our research did not reveal whether MNEs should apply predictive analytics while SMEs should apply descriptive analytics to sense the market. Such research could evoke interesting and useful findings for organisations.

Finally, our sample included eight companies that applied prescriptive analytics. We consider these representative, given that not many organisations currently apply this type of analytics [81]. However, we suggest that further research is required to understand if prescriptive analytics offers adequate insights for an organisation to enable (re)alignment of assets. Prescriptive analytics is a new field; as such, we recommend conducting further longitudinal research in future years, when data is likely to become available.

Limitations

The methodology applied here may have been an unsuitable use of NLP. In hindsight, to reduce the number of papers in our sample, we could have read the articles, instead of using advanced algorithms. Advanced algorithms can be useful to extract structured information from unstructured data if the sample size is large—that is, in the millions of documents. In that case, advanced algorithms can find patterns and relationships among concepts in a fraction of the time it would take a human. However, in our research, the sample size was too small to benefit from this. Nevertheless, it was an interesting exercise that demonstrated the potential of this approach. Future scholars can benefit from advanced algorithms when they are dealing with a large number of documents and unstructured data.

A related limitation is the overall low number of articles from high-impact journals that form part of our sample. Unfortunately, such papers were not available and we had to include journals of a lower rank. However, the number of case studies on big data analytics is likely to increase over time. Future research will benefit from more case studies and more high-impact journal publications.

Conclusion

To explain black swans, Taleb [19, P40] employed the metaphor of the turkey:

> Consider a turkey that is fed every day, every single feeding will firm up the bird's belief that it is the general rule of life to be fed every day by friendly members of the human race 'looking out for its best interests', as a politician would say. On the afternoon of the Wednesday before Thanksgiving, something unexpected will happen to the turkey. It will incur a revision of belief. Consider that [the turkey's] feeling of safety reached its maximum when the risk was at the highest!

The same goes for organisations that believe that if something has worked in the past, it will continue to do so in the future, until 'well, it unexpectedly no longer does' [19, P41]. If organisations want to be around tomorrow, they should avoid being a turkey. In times of ambiguity and uncertainty, big data analytics enables organisations to sense and seize opportunities. Using large amounts of structured and unstructured data and applying it to advanced analytics enables organisations to understand their environment and seize opportunities, which enables them to remain competitive and avoid being the turkey.

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