Sociomateriality in the age of emerging information technologies: How big data analytics, blockchain and artificial intelligence affect organisations

By

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Certificate of original authorship

I, Mark van Rijmenam, declare that this thesis, is submitted in fulfilment of the requirements for the award of the Degree of Doctor of Philosophy in the field of Management at the Faculty of Business at the University of Technology Sydney. This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Thesis format

This thesis is a thesis by publication. That means that this thesis consists of three papers that are published/publishable, which are linked together using the introduction, literature review and discussion. It is structured as a single manuscript and the introduction, literature, the three papers, the discussion and the conclusion are separate chapters. The literature review as well as the three papers are distinct, but they are linked in a logical and coherent way.

Papers included & statement of contribution

The following papers are included in this thesis:

	Title	Lead author	Co-author 1	Co-author 2	Co-author 3
Paper 1	Avoid being the turkey: How Big Data analytics changes the game of strategy in times of ambiguity and uncertainty – published in Long Range Planning	Mark van Rijmenam	Tatiana Erekhinskaya, Lymba Corporation, United States – assisting with the data analysis using machine learning and NLP. Contribution approximately 20%	Assoc. Prof. Jochen Schweitzer, University of Technology Sydney, Australia – Primary PhD supervisor providing feedback	Prof. Mary-Anne Williams, University of Technology Sydney, Australia – PhD Co-supervisor providing feedback
Paper 2	A Distributed Future: How Blockchain Changes Organisation Design – under review with Group & Organization Management	Mark van Rijmenam	Assoc. Prof. Jochen Schweitzer, University of Technology Sydney, Australia – Primary PhD supervisor providing feedback	Prof. Mary-Anne Williams, University of Technology Sydney, Australia – PhD Co-supervisor providing feedback	
Paper 3	How to build responsible AI? Lessons for governance from a conversation with Tay – Under review with California Management Review	Mark van Rijmenam	Assoc. Prof. Jochen Schweitzer, University of Technology Sydney, Australia – Primary PhD supervisor providing feedback	Prof. Mary-Anne Williams, University of Technology Sydney, Australia – PhD Co-supervisor providing feedback	

The above-stated information is correct:

Mark van Rijmenam	Tatiana Erekhinskaya	Associate Prof. Jochen Schweitzer	Prof. Mary-Anne Williams
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Table 1: Papers and contribution of co-authors

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Abstract

Emerging information technologies (EIT), such as big data analytics, blockchain and artificial intelligence (AI), challenge organisation design and strategic management, and bring the role of data in organising to the fore. Big data analytics empower consumers and employees, resulting in open strategy and a better understanding of the changing environment. Blockchain enables peer-to-peer collaboration and trustless interactions. And, AI facilitates new and different levels of involvement among human and artificial actors. From these interactions and responses, new modes of organising are emerging, where technology facilitates collaboration between stakeholders and where human-to-human interactions are increasingly replaced with human-to-machine and even machine-to-machine interactions. In this doctoral research, I use the theory of sociomateriality to untangle the social and material when dealing with EIT within organisations. I endeavour to explore these theoretical issues and present a new understanding of the relationships between the social, material and artificial.

Addressing this context, my research consists of three studies. Each study is arranged as a standalone paper. In the first study, I investigate how big data analytics affect can be used to better understand the changing organisational environment. The second study looks at how blockchain can result in new forms of organisational design and how it changes decision-making. In the third study, I seek to answer how organisations can ensure that artificial intelligence performs as planned. The results are discussed and made tangible by exploring how the social, material and artificial are changing collaboration among those actors involved in organisations.

I adopt three methodologies. The first study is a meta-synthesis of 101 peer-reviewed papers. The second study is conceptual and in the third study, I use qualitative research methodologies to interview managers of organisations who developed conversational AI.

The significance of this research is twofold. First, my academic contribution lies in understanding how big data analytics affect strategic management theory in general, and dynamic capabilities literature in particular; how blockchain requires us to rethink organisation design theory, and how agency theory can help when dealing with artificial actors. Also, I argue for the addition of the artificial as an independent actant in organisation design theories. Second, my findings inform organisational practice in terms of how to design organisations using EIT in an increasingly data-driven world. The key thesis underlying this research is that emerging information technologies change how we organise activities within organisations.

Acronyms

AGI: Artificial General Intelligence

AI: Artificial Intelligence

ANT: Actor-Network Theory

CEV: Coherent Extrapolated Volition

DAO: Decentralised Autonomous Organisation

DApp: Decentralised Application

DARPA: Defense Advanced Research Projects Agency

DNS: Domain Name Servers

DQM: Data Quality Management

EIT: emerging information technologies

ETH: Ethics

FAQ: Frequently asked questions

GE: General Electric

HMN: Human-Machine Network

ICB: Industry Classification Benchmark

IPFS: InterPlanetary File System

IoT: Internet of Things

IT: Information Technology

KPI: Key Performance Indicator

MDM: Master Data Management

MNE: Multinational Enterprise

NAI: Narrow Artificial Intelligence

NLP: Natural Language Processing

PBFT: Practical Byzantine Fault Tolerance

PKI: Public Key Infrastructure

PoS: Proof of Stake

PoW: Proof of Work

SAI: Super Artificial Intelligence

SHA: Secure Hash Algorithm

SME: Small and Medium Enterprise

SMS: Strategic Management Society

SSL: Secure Sockets Layer

USC: Utility Settlement Coin

UTS: University of Technology, Sydney

XAI: Explainable AI

Y2K: Year 2000

Chapter 1: Emerging information technologies

In business environments where accelerated change is the only constant (Hajkowicz et al. 2016), companies remain competitive not only by focusing on excellence in day-to-day business operations but also by being innovative and adaptive to change. Due to the availability of new and emerging information technologies (EIT)—such as cloud-based computing, big data analytics, artificial intelligence (AI) and blockchain—in recent years it has become easier to compete as a newcomer in traditionally closed markets (Landis and Blacharski 2013). This means the ability to cope with, react to, and anticipate industry disruption becomes an important capability (or skill) for organisations wishing to remain competitive. Organisations seeking competitive advantage in such environments focus on excelling in day-to-day business operations. They can detect, anticipate and respond to disruptive changes (De Meyer, Loch, and Pich 2002, Petrick and Martinelli 2012), while displaying industry leadership and managing shifting behaviours of stakeholders (Buysse and Verbeke 2003). This ability has been coined 'organisational ambidexterity' (O Reilly and Tushman 2004, Raisch et al. 2009) and is considered especially important when facing environmental ambiguity or deep uncertainty (Teece, Peteraf, and Leih 2016, Bennett and Lemoine 2014). For organisations to achieve ambidexterity, they rely on data as a key resource for their business and develop data-driven business models (Hartmann et al. 2016). Such organisations use a variety of internal and external data sources, apply a variety of activities to that data, including processing, analysing and visualising, and use the insights of those activities to develop new products and services and target the right customers at the right moment (Hartmann et al. 2016). For many, this requires a different mindset (Gurbaxani 2016), as a great deal of organisations still base their decisions on experience and intuition instead of data analytics (Khatri and Ng 2000, PWC 2015).

This research focuses on the organisational and management implications of three EITs: big data analytics, blockchain and AI. EITs are challenging common industry practices (Landis and Blacharski 2013), organisation design and strategic management, and gradually turning organisations into a data organisation (Hartmann et al. 2016, Gurbaxani 2016). Big data analytics are central, as all new technology now creates data and to gain insights from that data, analytics are required. Analytics are used to interpret data regardless of the volume, velocity or variety. Blockchain is examined because of its potential to fundamentally change how we deal with data (Shrier, Wu, and Pentland 2016) and because the cryptography used in its distributed ledger technology affects organisation design, decision-making capabilities and existing power structures (Swan 2015b). Finally, AI is addressed because the mathematical formulae that make up algorithms rely on data to automate decision making and improve business (Luca, Kleinberg, and Mullainathan 2016), resulting in an algorithmic business where algorithms are an essential part of doing business that run multiple aspects of organisations to make sense of data without the intervention of humans (Prentice 2016).

Exactly how these technologies change an organisation depends on the technology as well as the social actions of the people responding to that technology (Leonardi 2012). As humans interact with technology in different contexts, it changes their behaviour and that of organisations accordingly (Orlikowski 2000). Consequently, organisational change requires breaking down old habits and values and altering high impact systems such as decision-making capabilities (Kikulis, Slack, and Hinings 1995). Technology startups have long understood this and have developed an absorptive capacity and ‘overall innovation capability’ (Assink 2006, 227). They value the opportunity to collect and analyse data and create organisations that are more agile and flexible (Croll and Yoskovitz 2013), resulting in digital organisations with data at the heart of their business (Davis 2015). With a data-driven business come new actors, resulting in new ways of collaboration among those actors involved (Swan 2015b, Tsvetkova et al. 2017, Yoo et al. 2012, Grossman 2016). Such changes go along with the need to adopt a different mindset, which for many entails radical change (Schwab and Smadja 1995, McAfee et al. 2012, Grossman and Siegel 2014).

To understand how collaboration changes among actors in data-driven organisations, I use the lens of sociomateriality. The theory of sociomateriality is helpful in investigating the effect of EITs on organisation design and strategy as Information Technology (IT) is considered a social phenomenon (Orlikowski and Robey 1991) and how it is used depends on the context (Weißenfels et al. 2016, Orlikowski and Robey 1991). Organisations and technology are both social and material (Leonardi 2012), which is why the theory of sociomateriality can help us understand how these change when non-human actors are brought into the interaction.

However, because organisations are social, they respond differently to the need for change due to contextual variables such as environment, size and the technology adopted. Some organisations will exhibit reorientation behaviour, while others will showcase abortive movements or be reluctant to change (Greenwood and Hinings 1988, Orlikowski 2000). For example, online film distribution, digital photography and online book retailing have seen businesses like Blockbuster, Kodak and Borders become well-known instances of how once successful companies lacked the innovation mindset needed to respond to emerging technological change (Anthony

2016). Successful organisations continuously adapt to and exploit new, more advanced technologies to survive (Huber 1990b). Newcomers, such as Instagram, Netflix and Amazon, have shown such reorientation behaviour to leverage (technological) opportunities ignored or overlooked by others (Garud, Hardy, and Maguire 2013). Hence, to avoid a ‘Kodak moment’ it is vital to develop the capacity to detect, anticipate and respond in a timely manner to market changes and competitive pressures.

Contemporary technology startups, in particular, seem to value the possibility of collecting and analysing data to create new organisations and business models that are more agile and successful than existing organisations (Croll and Yoskovitz 2013). Hence, these new market entrants often take a different approach to organisation design (Christensen, Raynor, and McDonald 2015), which Miles et al. (2010, 2) argue is due to ‘a complex pattern of knowledge-driven dynamics’. This relates to the ability of companies to leverage new technologies and experiment with new approaches in an effort to benefit from opportunities resulting from a constantly changing global market. Such newcomers, who sometimes experience exponential growth, are usually characterised by a so-called platform approach to organisational design. Many of these new digital platform organisations leverage their technological advantage to affect and challenge incumbents (Romero and Molina 2011). Understanding how they do so could help incumbents remain competitive when challenged by these new digital platform organisations. According to Yoo et al. (2012), the emergence of data-driven platform organisations, such as Uber and AirBnB, has several implications, including the increased importance of data governance due to extensive sharing of data and processes across organisational boundaries, as well as achieving the delicate balance between generativity and control. This balance between power and empowerment seems to be shifting in new data-driven platform organisations (Grossman 2016), which consequently creates a shift in collaboration among organisational actors involved. It does this by 1) including previously excluded actors such as customers or competitors (Snow et al. 2011); and 2) by moving from pure human-to-human interactions to human-to-machine interactions and, increasingly, even machine-to-machine interactions (Swan 2015b, Tsvetkova et al. 2017).

As a result, organisations have new opportunities to collaborate and change their strategic management capabilities and choices. This requires a different mindset within organisations as a whole, as they need to rethink internal processes and structures to enable these new ways of cooperation among those actors (human and artificial) involved (Hoc 2000) to ensure continued productivity growth (Schuh et al. 2014). Consequently, to be able to incorporate EITs, organisations need to be thinking like software companies; that is, see themselves as a data company (Gurbaxani 2016), instead of, for example, a car maker, consumer goods producer or travel agent. Hence, organisations should aim to codify proprietary knowhow (Gurbaxani 2016); that is, turn existing analogue processes into digital processes that can be analysed and build a digital platform to grow the business.

Developing a digital platform not only offers new revenue streams and continuous growth opportunities, but it also allows companies to create new partnerships with previously excluded partners. Snow et al. (2011) refer to this as collaborative communities, where organisations that want to succeed will have to share knowledge and engage in collaborative relationships with industry partners to drive innovation, enabled by data and data related technologies (Kitchin 2014). These data and data related technologies allow organisations to affiliate with not only industry partners but any previously excluded actor, whether human or machine. The result is the emergence of new organisational designs, including that of a Decentralised Autonomous Organisation (DAO), which uses the blockchain and smart contracts to establish governance without management or employees, run completely by computer code (Garrod 2016).

With new types of organisational design emerging, collaboration among actors is also changing. Although those actors involved in an organisation have never been limited to human actors (Latour 1996b), new technologies result in networks that combine social participation and machine-based computation (Shadbolt et al. 2013, Smart, Simperl, and Shadbolt 2014, Buregio, Meira, and Rosa 2013). In such organisations, humans and machines interact with each other to produce synergistic effects, which are constantly evolving, and social interactions become more important, interactions less demanding, and machine-human interactions more prominent (Tsvetkova et al. 2017). Consequently, big data analytics, blockchain and AI result in new modes of collaboration among the actors involved, each offering a different take on collaboration. Big data analytics provides insights that empower customers and employees (Grossman 2016) , as when more people have access to information and knowledge, empowerment is a possibility (Foucault 1977). Thus, when organisations provide more people with access to knowledge through big data analytics, power is distributed more equally, enabling empowerment throughout an organisation and resulting in decentralised decision making (Fosso Wamba et al. 2015, Apte, Dietrich, and Fleming 2012, Berner, Graupner, and Maedche 2014, Galbraith 2014b). Conversely, blockchain enables peer-to-peer collaboration by creating distributed value (Kane 2016) through a network of peer-to-peer actors distributed across the globe, collaborating effortlessly and in real time to create value together for all actors in the network (Carroll and Bellotti 2015). It is governed by cryptography, consensus mechanisms and smart contracts (Mattila 2016). AI is about automating actions, enabling new forms of interaction among humans and machines, resulting in interactions with different levels of intensity and involvement (Tsvetkova et al. 2017). As such, organisations are engaged with various interactions among humans and machines, resulting in unexpected technical, social and ethical implications requiring complicated strategies (Callon 1990), which is why the theory of sociomateriality is useful in gaining a better understanding what this means for organisation design and strategy.

The aforementioned results in the research question for my study:

How do emerging information technologies change the interaction of organisations and technologies.

1.1 Aim and contributions of this research

The aim of this research is to investigate how EITs such as big data analytics, blockchain and AI challenge organisational design, strategy and governance (Shrier, Wu, and Pentland 2016, Swan 2015b, Luca, Kleinberg, and Mullainathan 2016, Prentice 2016). According to Orlikowski and Robey (1991), when dealing with IT, a redistribution of knowledge, power and conventions within organisations is likely. Therefore, I investigate how these technologies change collaboration among the actors involved—human, non-human and now also the artificial—to extend existing management theories. Using sociomateriality theory as the theoretical lens for this research offers an understanding of how these technologies influence the social and change collaboration among those actors involved. Importantly, it raises the issue of how to conceptualise and incorporate the artificial as an independent actor in organisation design theories. In addition, the research focuses on how big data analytics affects strategic management theory in general, and dynamic capabilities literature in particular; how blockchain requires us to rethink organisation design theory by redefining the *decentralised* and *autonomous* form of organisation design; and how agency theory helps us solve the principal–agent problem when dealing with artificial actors that behave differently than intended.

The three papers that are part of this thesis have been published or are under review with reputable journals. The first study is published in *Long Range Planning* (Van Rijmenam et al. 2018), while the second paper is under review with *Group & Organization Management* and the third paper is under review with *California Management Review*.

1.2 Thesis structure

This thesis is organised in seven chapters. In Chapter 2, I first discuss existing theories on how technology in general and IT in particular change organisations, and how the theory has evolved over the past decades. The objective of information system research is to understand how people think and respond when confronted with (new) technology. I apply a sociomateriality lens, discussing its development and current debates, to explain why the current developments in EIT require us to rethink existing theory on sociotechnical systems. I then discuss the influence of EIT on existing power and decision-making systems within organisations and how data related technologies are poised to restructure organisation design. This results in the introduction of a new actor, *the artificial*, and I explain how artificial agency affects existing sociomateriality theory. I then set out how to discuss the three studies to understand the impact of EITs on organisations.

Chapter 3 offers an overview of the research methodologies applied in each of the three papers. Each paper adopts a different methodology, including a meta-synthesis using Natural Language Processing (NLP) for the first paper, a conceptual approach for the second paper and in the third paper, I adopt the qualitative approach of semi-structured interviews.

The central research question will be answered using three studies, resulting in three papers that deal with the three chosen technologies: big data analytics, blockchain and AI. Chapter 4 houses the three complete papers. Each paper discusses a specific technology and how it will affect organisations. This enables me to understand how big data analytics, blockchain and AI can be applied, how they change collaboration among those actors involved, and what that means for existing organisations. As such, each of the three, separate papers contribute to an overall understanding of how EITs change the interaction of organisations and technologies:

Study 1: How can organisations apply big data analytics in dealing with ambiguity and uncertainty?

Study 2: How does blockchain result in new and disruptive forms of organisation design?

Study 3: How can organisations ensure responsible AI and prevent AI from harming those actors involved?

Chapter 5 then follows with a discussion on the insights from the three papers to show how collaboration among involved actors will actually change when dealing with EITs. I discuss my theoretical and practical contributions, the research limitation and offer an agenda for further research. Finally, Chapter 6 concludes this research.

Chapter 2: How technology changes organisations

The development and deployment of IT is a social phenomenon (Orlikowski and Robey 1991) and many scholars have discussed the impact of technology on organisations. Early scholars examined the challenges of manufacturing technology and their implications for management and decision making, such as Leavitt and Whisler (1958). In a classic study, Woodward (1965) considers the relationship between organisational structure and organisational performance, arguing there are specific organisational design responses to adopt/overcome the challenges of new technologies. The emphasis of these early studies was on how technology influenced organisational structures and production processes, especially in relation to manufacturing technology (Woodward 1965, Thompson 1967, Harvey 1968, Hickson, Pugh, and Pheysey 1969). Central to this earlier research was that the social and the technological were equal parts in organisational structures (Emery and Trist 1960, Bostrom and Heinen 1977). Another group of researchers focused on theorising the relationship between organisations and technology, and sought to view technology as having predictable impacts on organisations (Blau et al. 1976, Huber 1990b, Pfeffer and Leblebici 1977). These contingency scholars traditionally focused on the design of organisations, while sociotechnical scholars focused on the design of technology (Mueller, Renken, and van Den Heuvel 2016). Later, scholars moved from manufacturing technology to include a variety of other technologies (Glisson 1978, Perrow 1967) and viewing technologies as material determinants of organisations (Orlikowski 2009). Later research examined the effect of IT on organisations (Brynjolfsson and Hitt 1998, Huber 1990b, Ciborra 1996). Giddens (1984) then introduced the theory of structuration, arguing that there are two opposing traditions in terms of social reality: social reality is either subjective (with human actors as the focus of attention to understand how individuals create social worlds) or objective (the institutional properties influence human actions and social relationships over time). Both views of social reality are equally important (Orlikowski and Robey 1991). The theory of structuration argues for a duality of structure, rather than dualism between the objective and the subjective, where humans shape the world around them and the world shapes them. Giddens (1984) argues that human interactions consist of structures of meaning, power and moral frameworks, and if you wish to analyse human interactions, you should analyse these structures. The theory links how humans interpret behaviour, how they realise intentions, and what is appropriate conduct (Orlikowski and Robey 1991).

While early work in management and organisational studies considered the role and interaction of social systems and technological systems for organisational responses, this emphasis was lost in later years. Barley (1988) criticised the notion that technology is either a physical object or a social product, as it is both. This came back to the fore via the work of Barley (1986) and Orlikowski (1992) who argued that management scholars needed to again be attentive to the material and the social issues of organising. Barley (1986) used Giddens' (1984) structuration theory to argue for technology as the enabler between action and structure, contending that how actors use technologies could change organisational structure. Thus, technology can change action that can result in a changed organisational structure (such as centralisation or decision making). With the appearance of advanced IT, Huber (1990b) similarly argued for a revision of the existing organisation design theories as the first wave of advanced IT changed the nature of organisational design, intelligence and decision making. Other scholars expanded this line of inquiry and argument; for example, DeSanctis and Poole (1994) explain how technology and social interaction are related, whereby social structures are the norms and behaviours governing decision-making capabilities. Both Barley and DeSanctis and Poole assume 'technology uses mediated action and structure' (Leonardi 2013, P64), thereby offering new affordances or reconfiguring organisational structure. However, the effect of technology varies depending on the affordances that the technologies can provide; thus, sometimes enabling activities and sometimes limiting them (Mutch 2013). Although, with increased capabilities of EITs, this line becomes increasingly blurred.

Eventually, this resulted in the structurational model of technology developed by Orlikowski and Robey (1991). Taking Giddens' (1984) approach, they argue that context plays a role in structuration and technology can both facilitate and constrain social action, while human actors continuously shape IT so it remains flexible and is not a fixed constraint. The structurational model of technology considers the development and deployment of IT as a social phenomenon where social and material dimensions influence organisations. This model was aimed at helping researchers understand how IT is created, used and becomes institutionalised within organisations. Importantly, it articulated that IT is a product of human actions and a medium for human actions. Orlikowski and Robey (1991, 153) argue that 'technology can only condition and never determine social practices' as IT is constructed by human actions and objectified by institutionalisation. Whereas Barley (1986) and DeSanctis and Poole (1994) viewed action as the communication between people that was changed by technology, Orlikowski (1992) saw how people used technology as what constituted organisational structures; that is, technology in itself did not change structure, it was how people used it that was important. Notably, she argued that existing power balances determine the usage of technology within organisations and that powerful actors act with technologies to achieve certain organisational practices. Of course, people could ignore these, resulting in changes in structure, hence the name duality of technology (Orlikowski 1992). Nevertheless, she considered technologies as 'products of their time and organisational context' that reflect the 'knowledge, materials, interests and conditions at a given locus in history' (Orlikowski 1992, 30).

Orlikowski (1992) further posited that technologies have different degrees of interpretive flexibility, meaning there is flexibility in how people design, use and interpret technology. However, this flexibility is determined by the material affordances of the technology, the institutional context such as power, knowledge, the interest of human actors and time, as technology tends to become routinised within an organisation. With 'the generative and unbounded materiality' of EIT (Yoo 2013, 2), this notion becomes increasingly significant.

2.1 A sociomateriality view of new technologies

Later, Orlikowski (2000) expanded her views, resulting in the 'technology-in-practice' approach, arguing that patterns of how technology is used combine to form certain structures, thereby giving technology a more socialised view. However, this approach has been criticised for being too social a view where technology 'is subject to the whims of their users' (Leonardi 2013, 64), suggesting users can apply the technology as they deem suitable. This critique of an over-socialised view of technology's role in the process of structuration has resulted in various scholars attempting to bring technology back to the fore (Leonardi 2007, Svahn, Henfridsson, and Yoo 2009, Volkoff, Strong, and Elmes 2007, Jackson, Poole, and Kuhn 2002, Leonardi 2009) and treating it as a structural property (Leonardi 2013).

Barad (2003, 801) famously wrote: 'Language matters. Discourse matters. Culture matters. [..] the only thing that does not seem to matter is matter'. With this, she contested that objects do not have agency, rather people attribute agency to objects when they use them and it was time to focus more on the material (Barad 2003). A central component of her position was the concept of performativity, meaning something is performative when it contributes to the constitution of the reality it describes. As such, technologies exist in the 'realm of structure' and technology-in-use in the 'realm of action' (Leonardi 2013). This approach helped researchers discuss the materiality of objects (as in the physical or digital characteristics). Orlikowski (2007) responded to such critiques by introducing the sociomaterial perspective, thereby shifting away from technological artefacts and technologies-in-use to *the social* and *the material* and directing scholars more to the role of technology. When Orlikowski (2007) introduced the concept of sociomateriality, a reinvigorated interest and renewed academic discussion of the social and the material occurred.

According to Orlikowski (2007, 1435), the field of organisation studies had overlooked how organisations are bound up with 'material forms and spaces through which humans act and interact'. Therefore, she proposed the concept of sociomateriality. As people interact with each other—which influences technologies and technologies influence how people interact with each other—they are *constitutively entangled* (Orlikowski 2007). The social and the material are entangled and inextricably related, where the social shapes the materiality of technology and materiality is present in every phenomenon considered social (Orlikowski 2007, Leonardi 2012). Within the entanglement, the material influences the social and vice versa, and all organisational aspects are bound by the material (Orlikowski 2007), which becomes visible when dealing with online media where technology both facilitates and constrains the behaviour of media users (Napoli 2014).

Sociomateriality moved the analysis from the development of the material to the use of the material. It represents the enactment of activities combining materiality with institutions, norms and discourses; that is, with the social (Leonardi 2012). The technology is not sociomaterial but the practice in which it is embedded is (Orlikowski and Scott 2008). Social and material agencies become interlocked and produce technologies and organisations, although an agential cut (an analytical separation) is possible (Weißenfels et al. 2016). Barad (2007) expands this notion with the concept of the inseparability of the social and the material, stating that matter has no properties and only exists when it actively participates in a network.

Sociomateriality sees the material and the social as intrinsic to organising, which is why Orlikowski and Scott (2008) argue for entanglement of the social and the material when dealing with IT. With organisations increasingly subject to multiple, emerging, changing and interdependent (information) technologies, materiality becomes integral to everyday life (Orlikowski 2007). When that happens, it increasingly alters existing relationships and power balances (Dourish and Mazmanian 2011, Mazmanian, Cohn, and Dourish 2014). Social agency refers to how humans define and use technology, while material agency is the capacity of non-human actors to act without human intervention (Leonardi 2011). As such, social and material agencies both relate to actions, but they differ in intent. Social agency is a coordinated exercise to achieve certain goals, while material agents exercise agency using performativity (Barad 2003); that is, non-human actors do not have inherent intention (Taylor et al. 2001) and do not act to realise their own goals, as non-human actors do not have goals of their own making (Leonardi, Nardi, and Kallinikos 2012). Instead, people attribute agency to objects when they use them (Barad 2003) and they are free to enact technology in ways they deem necessary, so technology is at the discretion of human agents (Boudreau 2010).

Hence, performativity is a central idea within sociomateriality as it shows how relations and boundaries between technologies and humans are enacted in practice (recurrent activities) and therefore, are not fixed or pre-given (Orlikowski and Scott 2008). Performativity came into the sociomateriality literature because sociomateriality is all about actions and performativity shifts the discussions from descriptions to actions; that is, it suggests an agent is performative when it contributes to the structure that it describes (Barad 2003). Callon and Muniesa (2005) use performativity to understand algorithmic trading: models that described the world of option pricing were later used in algorithms, and thereby enacted that world. The theory was used to build the market it described. As such, the models contribute to the development of the reality they first described. Callon (1984) refers to this as an *interessement* agency that helps start a process, or mediate user participation, to achieve a certain objective or to make sense of and engage with a changing environment. From this stance, neither human nor material agency should be given priority when dealing with how people reach their objectives (Callon 1990, Latour 1992) as 'each contributes equally to shaping the other' (Leonardi 2011, 150). As such, humans and technologies acquire form, capabilities and attributes through their interpenetration. The social and the material are inseparable (Callon 1990, Latour 1992). Agency, therefore, is an effect of the relations and interactions between human and non-human agencies in a network (Stang Våland and Georg 2014). Viewed from this perspective, precisely what material artefacts are is important, as artefacts are more than an organisations' representations. They also help create the organisation when users interact with it and develop a new understanding of that organisation (Stang Våland and Georg 2014).

Subsequently, material artefacts mediate and shape interactions and affect internal power relations. Since the social and the material are directly linked to power when strategising (Balogun et al. 2014), incorporating the notion of power in sociomateriality is important (Leonardi and Barley 2010). Power dimensions play a role in changing or maintaining a specific organisational model (Greenwood and Hinings 1988), whereby some actors have more influence than others in how technology is used (Orlikowski et al. 1995), thereby reinforcing existing power structures. However, the adoption of new technologies can also lead to conflict and change existing power distributions (Orlikowski and Robey 1991, Assink 2006, Leonardi 2009), social orders and established patterns of interactions among groups (Leonardi and Barley 2010) since new technologies often result in actors having access to new information or previously excluded information. Having access to new and more information changes how people behave, the tasks they conduct and changes communication among people, which can trigger changes in interaction patterns and work roles (Orlikowski 1996, Leonardi 2012). As such, technological change can result in political change, changes in the social order and shifting existing power balances within the organisations (Barley 1986). Different EITs will have different implications and trigger different changes in existing interactions. Therefore, to understand how new technologies affect an existing organisational model, it is important to understand the intricacies of the technology being implemented. Big data analytics, for example, can lead to empowerment, because, as Zuboff (1988, 308) argues, 'the more blurred the distinction between what workers know and what managers know, the more fragile and pointless any traditional relationships of domination and subordination between them will become’. People are flexible to change their routines if required when dealing with technologies (Leonardi 2011) and, therefore, technology can cause relations among people to become less hierarchical and more collaborative (Edmondson, Bohmer, and Pisano 2001). As such, sociomaterial arrangements related to EITs, constitute certain changing power relations; those that previously were excluded from information, can, thanks to digitalisation, obtain access to valuable insights and information. Or as Yoo (2012, 5) argues, ‘digitalisation has brought a fundamental shift in the power balance between material and immaterial’, thereby altering existing relationships (Dourish and Mazmanian 2011) and decision-making processes (Barley 1986, Huber 1990b).

Power and decision-making processes create standards of behaviour and interactions (Kikulis, Slack, and Hinings 1995), as well as existing communication processes, norms, routines and common perceptions (DeSanctis and Poole 1994, Leonardi 2011). These determine how people apply (new) technologies to achieve their goals, also known as human agency (Leonardi and Barley 2010, Leonardi 2011) or social agency (Weißenfels et al. 2016, Leonardi, Nardi, and Kallinikos 2012). Conversely, material agency is known as how technology acts when human actors interact with it (Weißenfels et al. 2016), or how a technology's materiality acts (Leonardi, Nardi, and Kallinikos 2012). In other words, agency is a capacity realised by human and non-human actors, and it is an effect of the relations and interactions between those human and non-human agencies in a network (Latour 2005a). Hence, as social and material agents interact, agency shifts and they develop a complex web of sociomateriality (Orlikowski and Scott 2008). Understanding this difference between social and material agency will help to understand how EITs interact with them. However, sociomateriality is an emerging stream of research and, therefore, there are some fierce debates taking place among scholars of sociomateriality (Cecez-Kecmanovic et al. 2014).

2.2 Sociomateriality as a lens to understand EIT

The concept of sociomateriality is viewed as 'one of the most important ontological trends of the past years' (Mueller, Renken, and van Den Heuvel 2016, 69, Riemer and Johnston 2017). However, the emerging theory of sociomateriality still offers several challenges as there are two fierce debates going on among scholars (Cecez-Kecmanovic et al. 2014) that are important for our understanding of how we could view the EITs within organisational theory.

Since the entanglement of the social and the material, matter seems to matter (Carlile et al. 2013, Scott and Orlikowski 2012), but what defines matter when we talk about digital technologies is still up for debate. On the one side of the debate, Aristotle referred to materiality as the perceptible (that what can be perceived) and the intelligible (that which cannot be perceived) (Hassan 2016). Leonardi (2012) views IT as perceptible as people can interact with binary signals and hence it can be perceived. As such, he includes digital materials as material as they are available to all users in the same form. Even if the material features are not directly observable, as is the case with digital technologies, they still have material consequences and are, therefore, deemed material (Leonardi, Nardi, and Kallinikos 2012). In addition, with rapid advancements in digital technologies, form and function are increasingly becoming detached from matter as digital technologies consist of material resources of a granular level previously unthinkable. Hence, Leonardi, Nardi, and Kallinikos (2012) accept that matter can continue to transform and recombine in forms previously unthinkable as long as the (digital) material conditions and characteristics endure across differences in place and time. These material conditions are critical to enable IT (e.g., server farms) and determine the materiality of information representation; that is, the particular material forms of information (columns, records, numbers, algorithms etc.) (Dourish and Mazmanian 2011, Mazmanian, Cohn, and Dourish 2014).

On the other side of the debate, Yoo (2012), views digital artefacts as generative that continuously change and evolve as they cannot be contained, which in Leonardi's (2012) terms would mean that they are immaterial. In addition, Faulkner and Runde (2012) and Kallinikos (2012) suggest that some aspects of digital technology can be understood as immaterial as they have no weight and lack any spatial mode of being, meaning that IT cannot have any material agency associated with it. Despite that they play an active role in the material world, with significant consequences, there is no ‘thing’ (Pentland and Singh 2012).

The second important debate revolves around whether or not the social and the material are constitutively entangled. There is a great divide among scholars. On the one hand, scholars view the social and the material as inextricably linked and entangled and they see the social and the material as a true duality, an intertwining and entanglement of the two where there is no social without the material and vice versa (Barad 2003, Pickering et al. 2002, Orlikowski and Scott 2008). Within entanglement, the material influences the social and vice versa and all organisational aspects are bounded by the material (Orlikowski 2007). Actor-Network theorists concur with this stance, as they see any actor, human or non-human, as equivalent in semiotic terms (Callon 1990, Latour 1992). They argue that neither human nor material agency should be given priority when dealing with how people reach their objectives. They contribute equally to shaping the other, and there are no inherent differences between the social and the material, which Latour (2005a) refers to as the notion of flat ontology dictating that all objects or actors are alike and part of an intricate network that evolves. This approach of the social that is material and the material that is social, seeing them as inextricably related, is the theoretical foundation of agential realism (Leonardi 2013). Although the social and the material are inseparable and similar, an agential cut (an analytical separation) is possible (Weißenfels et al. 2016).

Not all scholars adhere to this approach (Mutch 2013, Faulkner and Runde 2012). Mutch (2013) urges for reflection and introduces the critical realist approach to sociomateriality as there are several problems with agential realism, including the lack of explanatory power, the difficulty to use subject-object dualism in empirical studies and because it treats all relations as mutually constitutive or co-dependent. Critical realism is a philosophical approach (Bhaskar 1979), suggesting possible existence of realities beyond our conscious experience; that is, mental states and attributes (such as meanings and intentions) that are part of the real world, despite not being directly observable—resulting in possibly different perspectives on reality (Maxwell 2012). Within the critical realist approach, structure predates actions that transforms it, and structural explanations postdate actions—a position referred to as 'analytical dualism', whereby structure and agency interact while remaining distinct, enabling separate analysis of both structure and action (Leonardi 2013). Consequently, technology is enacted by actions of the social and the social and the material only meet in practice and their interactions determine how the practice plays out (Mutch 2013). Suchman (2007) refers to this as the idea of assemblage, where the social and the material influence each other over time, where action patterns change depending on time and/or context and different assemblages result in different sociomaterial practices (Weißenfels et al. 2016). Critical realism is an alternative 'to show the importance of the relationship between the social and the material and of exploring that relationship' (Mutch 2013, 38) and it treats materiality separate from the social context it is part of. Within the critical realist approach, sociomateriality is different from materiality as it sees materiality as a constitutive element of the social and vice versa. Time is an important notion within the critical realism stance, as it views social and material agencies imbricating over time as it is 'through exercise of agency that action and structure are put into conversation' (Leonardi 2013, 70).

Within agential realism, the social and the material are interpenetrated and entangled, while a critical realist approach sees the social and the material as separate, becoming entangled by means of action (Tunçalp 2016). As Leonardi (2013, 69) explains, 'the main crux of the difference in theoretical foundation offered by agential realism and critical realism is that the former treats the 'sociomaterial' as something that pre-exists people's perceptions of it while the latter argues that the 'social' and the 'material' are independent entities that become 'sociomaterial' as they are put into relationship with one another through human action'; that is, within the critical realist approach, the social and the material can exist without the other (Tunçalp 2016). It may seem that both sides are far apart but fortunately, Leonardi (2011) offers some middle ground in the debate with his metaphor of imbrication, which is the interweaving of human and material agencies (Taylor 2001, Ciborra 2006): social and material agencies are not so much entangled but more interwoven, like roof tiles interweave on a roof; there are distinct overlapping patterns. Human agency is the dominant factor and shapes its goals with the material, but the social and the material are analytically and ontologically separable (Leonardi 2011, Riemer and Johnston 2017). As such, the concept of imbrication maintains the distinction between human and material agencies related to intentionality but recognises the differences related to synergistic interaction (Leonardi 2011).

What constitutes the social and the material and whether or not the social and the material are entangled, becomes especially relevant when dealing with EITs, due to the introduction of non-human, intelligent, actors. Crucial to understanding why, is a clear understanding and definition of what technology is in the first place. Therefore, in the next section, I will explore what technology is in the context of EIT.

2.3 The concept of technology in organisation and management studies

Despite many years of debates, there is still no clear definition of technology (Hassan 2016, Orlikowski and Scott 2008) and whether IT constitutes the material or the immaterial. Materiality such as chairs, tables, books, buildings, pens, data or computers can be perceived as technology (Orlikowski 2007) so are columns, records, numbers or algorithms (Dourish and Mazmanian 2011, Mazmanian, Cohn, and Dourish 2014) but since these digital elements have no weight and lack any spatial mode of being, they could be considered immaterial (Kallinikos 2012, Faulkner and Runde 2012). When a second wave of advanced Information Technologies appeared, this brought new fuel to the debate whether what is material and immaterial. In a now classic work, *The Sciences of the Artificial*, Herbert Simon (1996) identified digital elements as artificial things, which are synthesised by humans and, therefore, not natural. He argued that to better understand how the artificial will behave, a process of simulation may be used, because the behaviour of computers is governed by simple laws where the complexity results from the environment.

Huber (1990b, 7) defined IT as 'rationality-enhancing technology that transmits, manipulates, analyses or exploits digital information and thereby facilitates easier, cheaper and more controlled communication and information transfer, which will enhance organisational intelligence and reduce management levels in decision-making'. Roberts and Grabowski (1999) added to this that technology consists of three aspects: mechanical systems (hardware), human systems (skills and human energy) and knowledge systems (abstract meanings and concepts), whereby they see technology as descriptive (the type and role of technology within organisations) and relational (the relation between technology and structure). Hence, as people use technology it influences their behaviour, which influences how they use the technology (Orlikowski 2000) and it is observed as an external force that drives change within an organisation (Orlikowski 2009). As such, technology is not neutral but an integral and material part of constituting a certain phenomenon (Orlikowski 2009). As a result, the terms 'material' and 'technology' are often used interchangeably (Faulkner and Runde 2012) and Leonardi, Nardi, and Kallinikos (2012) actually view materiality as a mode of technology, instead of its essence.

Technology is the result of continuous interactions of human actors, actions, choices, social histories and institutional contexts, and its material artefacts are socially defined, produced, and only relevant to people engaging with them (Orlikowski 2009). Technology would produce certain identifiable impacts on organisations (Orlikowski 2009); however, with technology rapidly becoming more complex and changing quickly, it becomes increasingly difficult for researchers to understand this impact (Orlikowski and Scott 2008). Also, with materiality only capturing part of the complexity of technology, Yoo (2012) argues for a new way of thinking, as today's technology has gone beyond the interpretative capabilities of traditional materiality (Leonardi, Nardi, and Kallinikos 2012).

In 1991, Orlikowski and Robey (1991) argued that IT has social and material properties; it is constructed by human actions, while objectified by institutionalisation. It offers a framework for human actors to understand their world, it is a medium for the construction of their social reality, and it contributes to human actions by objectifying knowledge and assumptions (Orlikowski and Robey 1991). Since materiality is at issue here, as well as its relationship with technology and the social, we need to explicate a new direction. Therefore, researching technology simply from a social and material perspective (Orlikowski and Robey 1991) may no longer be sufficient. After all, with complex 'technology' such as AI, and its capacity to (re)create new Information Technologies that is, more artificial intelligence, this might no longer be completely accurate and requires a way of theorising beyond interpretative capabilities of traditional sociomateriality (Leonardi, Nardi, and Kallinikos 2012). In addition, advanced software now has such fine-grained material characteristics (bits and bytes) that it has become pervasive, ambiguous and ever-present on a granular level previously unthinkable, such that technology includes all levels of material from completely artificial environments to miniaturised devices (Leonardi, Nardi, and Kallinikos 2012). As such, the materiality of technological artefacts has both material features, which might not be directly observable as is the case with software, and material consequences, whereby even beliefs and feelings might have material outcomes. Consequently, form and function are increasingly detached from matter (Leonardi, Nardi, and Kallinikos 2012). Therefore, despite digital technological artefacts having a material and materiality-relevant side, scholars have not yet accepted that matter can have strange forms that we may not be familiar with. In fact, emerging information technologies such as big data analytics, blockchain and (advanced) artificial intelligence are increasingly not human-made nor material, while growing in complexity. These technologies therefore significantly affect strategic management (Berner, Graupner, and Maedche 2014, George, Haas, and Pentland 2014), organisation design (Van Rijmenam and Ryan 2019, Seidel 2018, Galbraith 2014b, Swan 2015b), and governance practices (Asadi Someh et al. 2016, Bostrom 2014), amongst many other organisational and management issues. Consequently, due to the complexity involved *in* these new emerging information technologies, as opposed to the complexity provided by the environment (Simon 1996), it might require a new 'science of the artificial' (Yoo 2012, Simon 1996). This influences how we view technology today, as materiality only captures part of the complexity involved with EITs in general or with AI, big data analytics and blockchain in particular.

Moreover, existing structurational models do not offer much help, since they assume technology becomes stabilised over time, meaning human actions do not refine and modify technology (Orlikowski 2000), which in a world of self-learning algorithms using reinforced feedback loops, is no longer the case. In addition, the concept of technology-in-practice, explaining how people deal and interact with technology, does not help either, since it assumes that only humans deal with technology. Orlikowski (2000) views technology-in-practice as technology having material and cultural properties that affect how people use it. Technology can be constructed with certain materials and assumptions, but only when it is used by human actions does it structure those actions. When an actor decides to use a technology, the actor also decides how to interact with it and these interactions can be different over time (i.e., like driving a car in different countries with different rules). However, physical properties result in boundary conditions on how to use an artefact and the more it is integrated into a system, the narrower its alternative uses. Unfortunately, none of these concepts offer any guidance when dealing with EITs; for example, with AI and blockchain, non-human actions structure technology actions and technology even creates new technology, but also adopts and uses that technology. Finally, the use of technology is also influenced by the understanding of the user (Orlikowski 2000). When using technology, humans are influenced by the materiality of technology, those inscribed by the designer and previous users. In this case, previous use affects how technology is used, even if that might be in ways not intended by designers, human actors might continue to use it in that way (e.g., due to corporate pressure, unavailability of staff, users' expectations or because they become more knowledgeable about the technology). However, when dealing with EITs, in particular when dealing with AI, this is no longer the case. Artificial actors are not bound by corporate pressure or unavailability of staff and AI removes wrong, unsuccessful behaviour if it does not contribute to achieving its ultimate goal (Bostrom 2014).

Technology is not sociomaterial but the practice in which it is embedded and practised is 'the space in which the social and the material become entangled' (Orlikowski 2009). However, within this practice when no social is involved, as in the case of AI, does this entanglement still take place? How can we conceptualise this interaction when no social is involved but an intelligent actor that has been created by technology itself is? In the following section I explore understandings of AI as it relates to existing theorising on sociomateriality.

2.4 Understanding EIT and the introduction of the artificial

With rapid advancements in AI, organisations are also increasingly dealing with (intelligent) artificial actors, which require a different approach, since AI is fundamentally different from human intelligence (Ayoub and Payne 2016).

Intelligence is ‘the complex expression of a complex set of principles’ (Yudkowsky 2007, 389), which consists of multiple interdependent subsystems linked to each other. Intelligence exists because of evolution. It enables humans to model, predict and manipulate reality and reason backwards and forwards from a mental image (Yudkowsky 2007). Evolution created intelligence but evolution does not possess this foresight. Moreover, this evolutionary process is an unintelligent process, resulting in flaws in human intelligence (Yudkowsky 2008). Thanks to evolution, our brains evolved, potentially, not in the most optimised way, due to constraints such as food availability or trade-offs with other organs (Armstrong, Sandberg, and Bostrom 2012). However, AI is developed by intelligent beings, who possess the foresight that evolution was missing (Yudkowsky 2007). As such, AI will be developed with materials, hardware and software better optimised for intelligence (Armstrong, Sandberg, and Bostrom 2012). Consequently, there is no reason to believe that intelligent artificial actors will behave the same as human or material actors (Fallenstein and Soares 2015), which affects how scholars could theorise sociomateriality in the age of AI.

Evolving technologies result in evolving organisational processes and it is vital to understand how digital technologies and their specific (im)materialities entangle with the social and the material (Dourish and Mazmanian 2011). Especially, because the basic elements of computational systems, data and algorithms, have become central to everyday life and understanding these fundamentals (a research stream that has become known as *computational thinking*) and how they affect organisations is as important as understanding mathematics or logic (Dourish and Mazmanian 2011). In addition, as has become clear from this literature review, for decades, scholars have looked at how technology changes organisations from a human, or social, perspective.

However, with the advance of AI, I argue that it is time for scholars to start incorporating the artificial perspective, as it behaves so differently from human intelligence.

How technology is used depends on the context, and this can change at any time (Weißenfels et al. 2016, Orlikowski and Robey 1991), especially when dealing with AI as AI incorporates a great deal more context than humans ever could. However, only limited research has been conducted, and many questions arise when talking about the artificial. I do not intend to answer these questions but simply pose them to show the need for additional research. For example, what structures emerge when people interact with the artificial remains unclear for now. How do existing structures, common practices and culture determine the artificial and vice versa? How does the incorporation of the artificial within organisation change how organisations deal with new IT? What is artificial agency and how does it affect technology adoption, change collaboration and influence traditional organisational tasks such as decision making, strategising or organisational design, normally performed by humans? In addition, how do artificial actors affect technology, what are the motivations of artificial actors, and do artificial actors' motivation change over time when it learns more? To understand these questions and how the artificial affects sociomateriality, we need to more closely examine the artificial agent and artificial agency.

Traditional IT is at the whims of its users (Leonardi 2013) but artificial agents have the power to change behaviour and make decisions independently and autonomously, thereby changing the context without being subject to the whims of human action. With the increased availability of advanced algorithms and AI within organisations resulting in increased automation of tasks and jobs, the balance that exists between social and technological, as determined by Bostrom and Heinen (1977), seems to be shifting, in favour of the artificial. Advanced computer-assisted information processing technologies result in a reduction of human nodes in an information network; that is, would lead to flatter organisations (Huber 1990b). When dealing with AI, it is no longer always the case that humans can use the technology as they deem suitable, as AI can make decisions based on its internal logic and the outcome is often a given (Van Lent, Fisher, and Mancuso 2004, Luca, Kleinberg, and Mullainathan 2016). In addition, although Orlikowski and Robey (1991, 147) argued that social actions 'always involve interactions between humans', this is no longer true as today's artificial actors also interact with social artificial agents such as chatbots. Even more contrary to Taylor's et al. (2001) belief of machine artefacts not having inherent intentionality, when AI is combined with smart contracts and distributed ledger technology, the possibility appears of developing organisations that are completely built up with code, without management or employees involved—so-called DAOs—where artificial agents act completely autonomously with intentionality.

Organisations and technologies are both social and material, and the same goes for the artificial; it has both human agency and material agency, but at the same time it is difficult to label it as social or material. Artificially intelligent agents have the capacity to act autonomously in response to human and material agency. It is social as it is developed by humans and it is not social as increasingly artificial intelligent artefacts are created by artificial intelligent artefacts, without any human involvement (Le and Zoph 2017). Or as Ullman, describes (Smith 2018):

> “when programs pass into code and code passes into algorithms and then algorithms start to create new algorithms, it gets farther and farther from human agency. Software is released into a code universe which no one can fully understand”.

As such, AI behaves differently when interacting with humans and without humans and rapidly it is becoming more intelligent than humans (Bostrom 2014). Next to that, it is material as it consists of binaries that are perceptible by humans (Hassan 2016), but these material characteristics can change, unexpectedly, over time, ‘driven by large, varied and uncoordinated audiences’ (Zittrain 2006, P1980). The artificial continues to develop and evolve once designed, while what it does can remain the same, albeit becoming better over time. In addition, artificial agency can act on its own; it showcases intelligent behaviour, it has goals, can reason and monitor its behaviour (Bostrom 2014). It can even reproduce and evolve without the need for human action (Abadi and Andersen 2016, Lewis et al. 2017). As such, artificial agency is fundamentally different from material agency; hence, a new science of the artificial is indeed required (Yoo 2012, Yoo et al. 2012).

Developing a new way of dealing with the artificial in organisation studies is critical as increasingly the artificial is affecting organisations in multiple ways. Until now, the artificial has been viewed as part of technologies (such as chairs, buildings, books, pens, data computers) that affect organisations (Orlikowski 2007); however, since AI is fundamentally different from human intelligence, with artificial agents operating independently of humans, the artificial is deeply changing organisations and hence requires a new approach to deal with it in organisation studies.

Leonardi, Nardi, and Kallinikos (2012, 42) defined social agency as "coordinated human intentionality formed in partial response to perceptions of a technology's material agency" and material agency as "ways in which a technology's materiality acts. Material agency is activated as humans approach technology with particular intentions and decide which elements of its materiality to use at a given time” (2012, p.42). Neither of these definitions are sufficient for the artificial, and instead, I define artificial agency as *artificially intelligent actors that have the ability to act upon their own, distinct from and without further human intervention*. As artificial entities, they can exercise agency through their performativity, that is, by doing things that are out of control of users or other artificial or human agents. As such, I define artificial agency as *coordinated artificial intelligent intentionality formed in partial response to perceptions of human agency and material agency.*

2.5 Towards a tripartite analysis of sociomateriality

Current research on sociomateriality fails to explore the generative and constitutive rules of digital and artificial artefacts (Yoo 2012). The entanglement of the social and the material raises ethical questions of consequences, responsibility and accountability (Carlile et al. 2013). This requires further discussion, especially when dealing with artificial intelligent agents, as artificial agency becomes increasingly important. However, within all existing theories related to the entanglement of the social and the material, the artificial is missing. This is not surprising since there has only recently been a continuous stream of breakthroughs of AI, made possible through increased ‘computational capabilities, algorithm design and communication technology’ (Alfonseca et al. 2016, 1). Since artificial artefacts can now be created by artificial intelligent actors, the important characteristic of sociomateriality (agential realism) that technological artefacts are created by social action, which in turn shapes human action (Leonardi 2013), no longer applies. Thus, no longer are ‘all Information

Technologies created by people and the result of social processes' (Leonardi 2013, 69). However, the critical realist position does seem to confirm the possibility that some materials are not simultaneously social, as it treats materiality as separate from the social context it is part of (Leonardi 2013). Within agential realism, the social and the material are interpenetrated and entangled, while a critical realist approach sees the social and the material as separate, only becoming entangled by means of imbrication. As such, when one adopts critical realism as a foundation for the study of sociomateriality, it better allows for an additional, artificial, agent that can become entangled with the social and material through imbrication than the agential realist approach. It is like adding a roof tile to an existing roof. In addition, time is an important notion within the critical realism stance, as it views social and material agencies imbricating over time, being 'through exercise of agency that action and structure are put into conversation' (Leonardi 2013, 70). Time is also important in relation to the artificial. AI continuously changes over time, and improves based on new input it continuously receives, thereby changing its materiality but not its social usages (its objective or goal).

A new approach to sociomateriality, whereby not only the social and the material become entangled by means of action but in which it seems the artificial also becomes entangled with the social and the material by means of action, is represented in Figure 1. Within this tripartite, the social, the material and the artificial seem to imbricate over time and through an exercise of their agency. The social, the material and the artificial are independent entities (Shotter 2013, Leonardi 2013), they are analytically and ontologically separable, becoming sociomaterial when they are put into a relationship with one another through human, material or artificial agency. Separating the artificial from the material is required because it combines characteristics of the material and the social but is none of those. As such, seeing the artificial as an independent actor allows me to investigate the effect of EITs within organisations.

Within the proposed tripartite analysis of sociomateriality, the social creates the material and the artificial, while the material and the artificial influence the social. The material creates the artificial, while the artificial influences the material. The focus is on how the social, material and artificial agency influence each other and how they acquire form, capabilities and attributes through their interpenetration, and how they interact with each other. Relations and boundaries between the social, the material and the artificial are enacted in practice and are not fixed or pre-given; that is, the context matters. Since the impact of the artificial on organisations is growing, scholars need to understand the sociomaterial (re)configurations as they perform organisational realities. Within the tripartite analysis of sociomateriality, the notion of performativity remains relevant for understanding organisation design in times of artificial actors. These artificial actors are developed within a certain framework and based on certain models that, when set free in an organisation, will then influence that organisation and how other actors interact. As such, a tripartite analysis of sociomateriality will help scholars understand how humans, technology and artificial intelligence are interrelated with each other and how they affect each other in action.

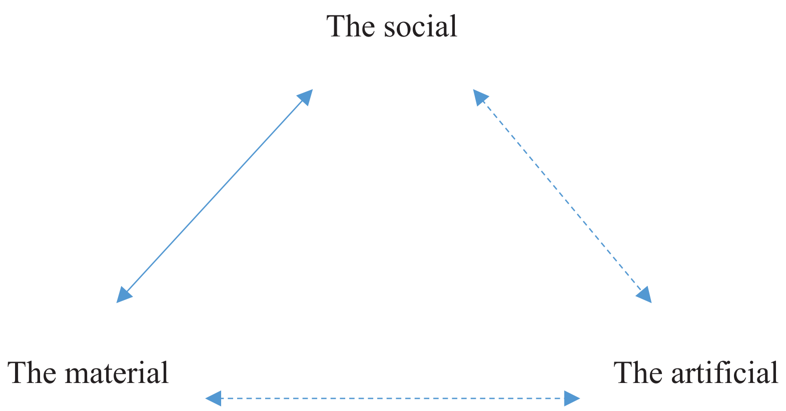

Figure 1: Tripartite of sociomateriality

This tripartite approach to sociomateriality, introducing the artificial as an independent actor, can assist future research investigations on the impact of emerging information technologies on organisations. It can help to understand the entanglement of the social, material and the artificial. Although much research has been done on the technical machinations of artificial intelligence contributing to its spread and usage, there is limited research done on how these newly developed applications and capabilities of EITs will affect strategic management, organisation design and governance practices. For example, conceptualising the artificial as an independent actor within organisations has implications for governance theories such as agency theory, as traditional governance practices involved with human actors might not apply to artificial actors. Therefore, in the second part of this doctoral study, I discuss three emerging information technologies individually, to understand their impact on organisation and theory. With this, I am to contribute to the literature of strategic management, organisation design and governance.

In my first study, I focus on how big data analytics influence organisations, management and employees and help organisations understand their environment. In this paper, I contribute to the existing dynamic capabilities literature by supporting and further expanding the notion of an analytical framework as required for the dynamic capabilities framework.

In the second study, I investigate what blockchain is, its potential influence on organisation design and how it is likely to result in new ways of collaboration among humans and artificial actors. As such, the paper contributes to an understanding how distributed ledger technology affects organisation design in general and decision-making and trust in particular.

Finally, in the third study, I investigate how the principal–agent problem can be overcome when dealing with artificial actors, thereby contributing to agency theory by expanding it to include not only human actors but also artificial, (super) intelligent, actors. In turn, the paper contributes to an understanding of how corporate governance can contribute to responsible AI.

Through the three distinct studies as part of this doctoral study, I aim to contribute to three theories in particular. This will help to better understand how EITs change the interaction of organisations and technologies. In the discussion, I aim to synthesise the results of the three studies and the literature review to understand how collaboration among those actors involved changes due to the application of big data analytics, blockchain and AI. Each paper aims to contribute to one theory:

Paper 1: Dynamic Capabilities Theory

Paper 2: Organisation Design Theory

Paper 3: Agency Theory

2.6 Theoretical framework

Big data analytics, blockchain and AI are three EITs that are likely to have an impact on organisation design and strategic management. Combined, these technologies could result in a radically new type of organisation, called the DAO. However, it is unclear to what extent these emerging technologies drive the rise of DAOs, since practically no research has been done in this area. Nevertheless, they will likely change existing human-to-human, human-to-machine and machine-to-machine networks and this research aims to understand how. Together, this indicates a gap in the literature, see Figure 2, in how organisations can leverage EITs and how it will change collaboration among those actors involved.

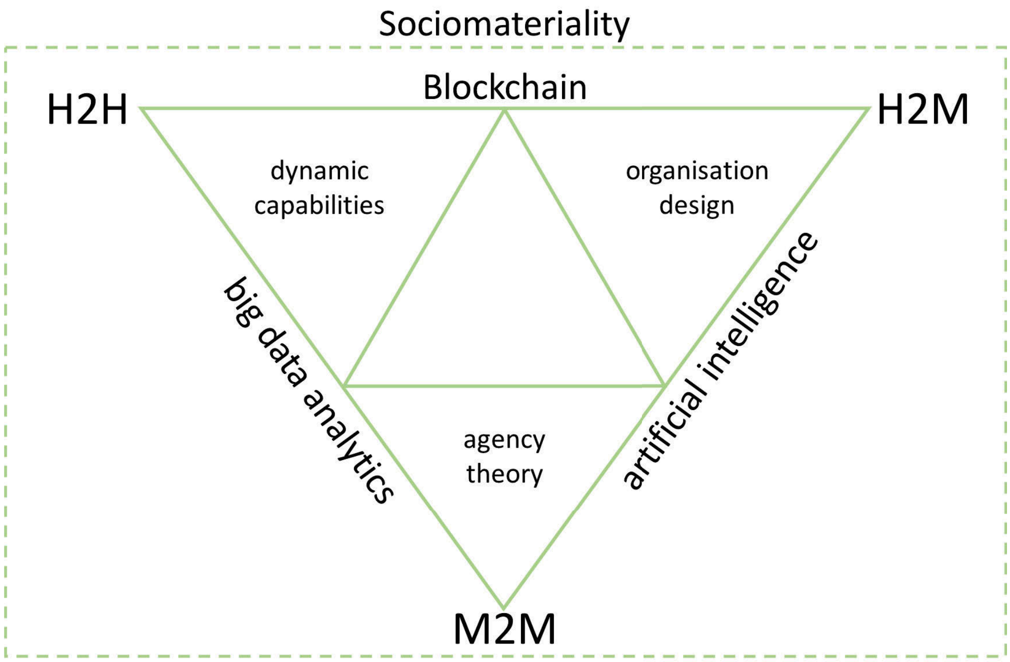

Figure 2: Relevant literature regarding data and data related technologies

The objective of this study is also to understand how EITs change the interactions among organisations and technologies and what the effect would be on collaboration among those actors involved when dealing with big data analytics, blockchain and AI. As such, after presenting the three papers that have been written for this doctoral thesis, I will discuss how actors interact with each other in an ever-changing network when faced with big data analytics, blockchain or AI. From that, I will offer a research agenda for how to deal with EITs.

Chapter 3: Methodology

The more sophisticated technologies are that are adopted, the more profound the impact will be on organisations (Huber 1990a). To understand the influence of EIT, a multiparadigm perspective (Hassard 1991) is used. Such a multiparadigm perspective can offer a more comprehensive understanding (Gioia and Pitre 1990, Morgan 1983, Alvesson, Hardy, and Harley 2008), which is especially useful in greenfield research areas such as blockchain or AI.

The rapidly changing technical, social and organisational world can be best understood using multiple perspectives, despite the challenge to apply the different paradigms equally (Alvesson, Hardy, and Harley 2008, Parker and McHugh 1991) as one paradigm is simply not sufficient to understand the transformation of sociotechnical systems (Rotmans, Kemp, and Van Asselt 2001). Taking such a multi-perspective approach, opens up new ways of thinking to understand how these EITs affect organisation and management theories and, therefore, the 'use of different perspectives is enlightening' (Alvesson, Hardy, and Harley 2008, 7).

As such, this study consists of three distinct, but related, studies, which I performed in a specific order to investigate the interactions among the social, the material and the artificial. The first paper investigates big data analytics; the second paper investigates blockchain and the third AI. I selected this order based on when the technology became mainstream and what type of interactions are involved. Laney (2001) first mentioned the term big data and big data analytics offers the social a better understanding of the environment while changing existing power dimensions, thereby affecting human-to-human interactions. Blockchain appeared in 2008 (Nakamoto 2008) and involves not only human-to-human but also human-to-machine interactions, where the material challenges existing practices of the social and the artificial. Finally, AI results in new human-to-machine and machine-to-machine interactions. In addition, while the first mentions of AI appeared in 1950 (Turing 1950) and the first warnings of societal implication started a few decades after that (Maybury 1990, Bloomfield 1987, Glushkov 1970), the academic discourse on the dangers of AI was truly reinvigorated only since 2014 (Bostrom 2014).

This research adopts three different research methodologies to understand how data and data related technologies affect organisation design and strategic management. To address the first research question, I conducted a meta-synthesis study on 101 peer-reviewed papers, where I looked at how big data analytics has been applied in a variety of organisations across a variety of industries. This allowed me to understand how big data analytics is used across industries in times of ambiguity and uncertainty. The second sub-research question resulted in a conceptual paper, since blockchain technology is so new there are not yet many fully implemented blockchain solutions. The third question has been investigated using qualitative research interviews at 20 organisations from nine countries that have applied or developed conversational AI within their organisation. This qualitative research consisted of semi-structured expert interviews and although it is industry agnostic, it is looking specifically at understanding how ethics have been applied in developing conversational AI. As such, this research allows a broad perspective on an existing technology, a conceptual perspective on a brand-new technology and a more specific perspective on existing technology that is back in the spotlight of academic scholars. Each paper explains the methodology in more detail.

3.1 Study 1: Meta-synthesis

In the first study, I carried out a meta-synthesis of 101 peer-reviewed academic articles that feature case studies of how organisations have applied various types of data analytics. A meta-synthesis analysis allows for drawing comparisons and conclusions from a collection of studies (Tranfield, Denyer, and Smart 2003). With the objective of wanting to understand how big data analytics enables organisations to sense, seize or transform the organisation to remain competitive, I developed a systematic selection procedure using a semantic data processing approach. The objective of the approach was to use big data analytics to answer the research question, and the steps included applying NLP and semantic analytics on the papers selected to understand the concepts within those papers. This resulted in a sample of 101 articles that feature relevant case studies of big data analytics. Each of these articles discusses an application of big data analytics within an organisation. The articles discuss a variety of cases within different contexts, which enabled me to synthesise these qualitative case studies (Hoon 2013) and understand different applications of big data analytics across different contexts. As Hoon (2013, P523) purports, such a meta-synthesis is considered inductive and aims to make ‘contributions beyond those achieved in the original studies’. I believe that the systematic selection procedure has produced a large enough sample to be demonstrative in respect of the existing research on big data analytics I seek to analyse. For a detailed description of the methodology applied in the first study, please refer to the first paper (see Section 4.1).

3.2 Study 2: Qualitative research

I adopted a qualitative research approach for the third paper to understand how different organisations deal with AI and how they can contribute to responsible AI. I interviewed one member from each of 20 organisations from different industries across the globe. I opted for a homogeneous group of interviewees, who shared several characteristics related to the research questions (DiCicco-Bloom and Crabtree 2006) such as having developed and implemented a human-facing chatbot. The initial interviewees were approached via personal connections or by connecting with the interviewees on LinkedIn.

Semi-structured interviews offer a deeper understanding of a certain phenomenon than purely quantitative methods (Silverman 2000), and the objective of the interviews was to explore the views, experiences and motivations of organisations concerning conversational AI (Gill et al. 2008). Performing qualitative research interviews enabled me to contribute to the literature based on the interviewees' experiences relating to AI. As such, the semi-structured interviews are the only data source for this qualitative research (DiCicco-Bloom and Crabtree 2006). To analyse the data, I applied a 'template approach' (DiCicco-Bloom and Crabtree 2006). I reviewed and identified text segments within the transcripts using a template (nodes) based on various theoretical perspectives, as discussed in the literature review of the third paper (Denzin and Lincoln 2011, Miller and Crabtree 1999). I used the text analysis software NVivo to support me in the data analysis and I followed Burnard's (1991) method of analysing interview transcripts in qualitative research.

Chapter 4: Three studies: big data analytics, blockchain and AI

This thesis consists of three separate studies:

Paper 1: *Avoid being the turkey: How big data analytics changes the game of strategy in times of ambiguity and uncertainty*—completed and published in *Long Range Planning*: https://www.sciencedirect.com/science/article/pii/S0024630117303606

Paper 2: *A distributed future: Where blockchain technology meets organisational design and decision-making*—completed and under review with *Group & Organization Management*

Paper 3: *How to build Responsible AI: A conversation with Tay and lessons for governance practices*—completed and under review with *California Management Review*

The first two studies discuss big data analytics and blockchain to understand how the characteristics of big data analytics (descriptive, predictive or prescriptive analytics) or blockchain (such as cryptography or smart contracts) affect the management and design of organisations. As such, dynamic capabilities theory and organisation design theory are used to investigate the impact of big data analytics and blockchain on organisations. The discourse on AI in the third paper is focused on the principal–agent problem and what organisations can do to overcome differences in goals and risks among agents and principals. It is focused on the effects on the organisation, whether it will be positive or negative; and on understanding how organisations can control artificial intelligence, which is why agency theory is applied to understand the differences in goals and risks among agents and principals when dealing with artificial actors.

4.1 Paper 1: 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 (Hajkowicz et al. 2016, 29). 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 (De Meyer, Loch, and Pich 2002, Petrick and Martinelli 2012), and they must do so while demonstrating industry leadership and managing shifting stakeholder behaviours (Buysse and Verbeke 2003). This ability, coined 'organisational ambidexterity' (O Reilly and Tushman 2004, Raisch et al. 2009), is especially important when facing environmental ambiguity or uncertainty (Teece, Peteraf, and Leih 2016, Bennett and Lemoine 2014). Environmental ambiguity refers to situations in which relationships are unclear and organisations face 'unknown unknowns' (Bennett and Lemoine 2014) 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 (Bennett and Lemoine 2014).

Ambidexterity is achieved through so called dynamic capabilities that help organisations understand a changing and uncertain environment (2007, 2012), which, according to Teece (2007), requires an analytical framework. Other scholars have suggested that data can assist organisations in understanding their environment (Brown 2008, George, Haas, and Pentland 2014). 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 (2015) 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 (O Reilly and Tushman 2004, Jansen et al. 2009, Volberda, Foss, and Lyles 2010). With the increasing diffusion of, emerging, digital technologies, incumbents are being forced out of business, especially in traditionally closed markets (Landis and Blacharski 2013). Businesses such as Blockbuster, Kodak and Borders serve as examples of once-successful companies that failed to respond to technological changes (Anthony 2016) 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 (Garud, Hardy, and Maguire 2013). Christensen et al. (2015) 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 (2007), 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.

As 'right answers can't be ferreted out' (Snowden and Boone 2007, P7), recognising technological market disruption in a complex context is no easy feat (Paap and Katz 2004). Often, disruptive innovations go unnoticed until it is too late (Carayannopoulos 2009). Taleb (2007) 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 (MacKay and Chia 2013). For example, the astronomer Clifford Stoll (1995) 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 (Castells 2014).

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 (Swan 2015a, Tapscott and Tapscott 2016). Some researchers suggest that entrepreneurial thinking allows organisations to better

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[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.

detect the emergence of black swans (Dewald 2016, Chen and Taylor 2009). Others, such as Taleb (2007), 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 (MacKay and Chia 2013, Taleb 2007). According to Taleb (2005), 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 (Teece, Peteraf, and Leih 2016, Bennett and Lemoine 2014) and are able to leverage opportunities to remain competitive (Kim and Pennings 2009). Hence, disruption and opportunities that may flow from the occurrence of black swans are not impossible to predict (Taleb 2007). In Hitt and Ireland’s (2001) view, recognising black swans is a matter of knowing where to look, having flexible processes in place, cultivating an entrepreneurial mindset and acting swiftly (Akkermans and Van Wassenhove 2013).

Recent research indicates that data can also assist in identifying black swans (Brown 2008, George, Haas, and Pentland 2014). In many organisations, the role of data has become increasingly important (Garud and Kumaraswamy 2005, Srivastava, Bartol, and Locke 2006) 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 (Galbraith 2014b). Grossman (2016) 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 (Berner, Graupner, and Maedche 2014). 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 (Laney 2001). Organisations and consumers already generate large amounts of data, which are predicted to grow exponentially (Singh and Rana 2013). In their seminal article 'Big Data and Management', George, Hass and Pentland (2014) argued that big data change how organisations are designed and managed, their culture and identity and how decisions are made (Brown 2008, George, Haas, and Pentland 2014). For many, the most likely path to achieve competitive advantage is via big data analytics (Barton and Court 2012). Hence, it is not only newcomers, such as Instagram, Netflix and Amazon, that can benefit from a data-driven approach (Goodwin 2015). 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 (Vahn 2014). In fact, some suggest that big data analytics have become a prerequisite to understanding the business environment and to remaining competitive (Bean 2016, Siemens and Long 2011). Studies show that big data analytics offer organisations competitive advantages (George, Haas, and Pentland 2014, Gabel and Tokarski 2014, Pigni, Piccoli, and Watson 2016, Fitzgerald 2016b) and that this affects organisational design (Galbraith 2014b, Grossman and Siegel 2014, Korhonen 2014, Slinger and Morrison 2014, Gabel and Tokarski 2014). 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 (2007) 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 (2007, 2012) suggested that dynamic capabilities require 'some kind of analytical framework' (Teece 2007, 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' (Hoon 2013, 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 (Puhvel 1984). 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 (2007) 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 (Taleb 2007); they are also a consequence of deliberate choices made by management (MacKay and Chia 2013). 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 (Suárez-Lledó 2011) and, as such, imply ambiguity and uncertainty.

Organisations that recognise black swans can create new opportunities and a competitive advantage (Kim and Pennings 2009), as it is at the edge of chaos and the unexpected that the greatest opportunities lie (Brown and Eisenhardt 1998). 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 (De Meyer, Loch, and Pich 2002). 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' (Petrick and Martinelli 2012, P2).

Kaisler and Armour (2013) 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 (Nafday 2009). As well as interpreting signals of a changing environment (Akkermans and Van Wassenhove 2013) 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) (Taleb 2005, Taleb 2007).

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 (Akkermans and Van Wassenhove 2013). 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 (Malone 1997, Galbraith 2014b), and when they have a flexible organisational design and the technological capabilities to innovate across time and space (Merrill 2015). 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 (Laney 2001). 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 (Galbraith 2014b, Grossman and Siegel 2014, Berner, Graupner, and Maedche 2014, Porter and Heppelmann 2015, Davenport, Barth, and Bean 2012, Davenport 2006, Bughin, Livingston, and Marwaha 2011): descriptive analytics, predictive analytics and prescriptive analytics (Vahn 2014, Evans and Lindner 2012, Kaisler et al. 2013, Delen and Demirkan 2013, LaValle et al. 2011, Larson and Chang 2016). Each stage offers insights that can improve and optimise performance and sustain competitive advantage (McAfee et al. 2012, Chluski and Ziora 2015, Prescott 2014, Vinod 2013, Kiron and Shockley 2011, Sharma, Mithas, and Kankanhalli 2014, Gobble 2013). 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 (Chen, Sain, and Guo 2012, Chui et al. 2011). 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 (Mortenson, Doherty, and Robinson 2015). 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 (LaValle et al. 2011). It is about the future and predicting what will happen (Mortenson, Doherty, and Robinson 2015); 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 (Gandomi and Haider 2015). There is an assumption that organisations that use predictive analytics gain competitive advantage because they can anticipate the future (Rod Koch CMA 2015); however, insufficient data and flaws or biases in algorithms may significantly harm organisations and their customers (O'Neil 2016).

Prescriptive analytics transform organisations. The final stage in understanding a business (Perugini and Perugini 2014), 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 (Delen and Demirkan 2013). 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. (Grossman 2016, Berner, Graupner, and Maedche 2014) 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 (Steven 1974) and access to resources or information not available anywhere else in the organisation (Saaty 1990). According to Bacon (1878), knowledge is a form of power that can be gained from power (Foucault 1977). However, when data and information are widely accessible in real-time, the power balance shifts (Grossman 2016) 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 (Galbraith 2014b, Fosso Wamba et al. 2015, Apte, Dietrich, and Fleming 2012, Berner, Graupner, and Maedche 2014). Malone (1997) 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 (Galbraith 2014b), as real-time insights enable anyone, not only executives, to make decisions rapidly, resulting in more agile companies (Galbraith 2014b, Grossman and Siegel 2014, Berner, Graupner, and Maedche 2014, Porter and Heppelmann 2015, George, Haas, and Pentland 2014).

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 (1994) described dynamic capabilities as those capabilities that enable organisations to develop new products and services in changing market circumstances to gain competitive advantages (Eisenhardt and Martin 2000, Zahra, Sapienza, and Davidsson 2006, Peteraf, Di Stefano, and Verona 2013). According to Teece (2007), 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 (Galunic and Eisenhardt 2001) and the agility to manage deep uncertainty (Teece, Peteraf, and Leih 2016, Teece, Pisano, and Shuen 1997a). Zollo and Winter (Zollo and Winter 2002) 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 (Teece 2007), which can give an organisation the ability to transform accordingly. Dynamic capabilities must be integrated, developed or reconfigured depending on how circumstances change (Teece, Pisano, and Shuen 1997b, Lavie 2006). Such capabilities emerge by learning from mistakes, practise and experience (Eisenhardt and Martin 2000, Makadok 2001). Teece (2007) considered dynamic capabilities particularly relevant for organisations that are receptive to market and technological developments (Teece, Pisano, and Shuen 1997b), especially within fast-moving environments that involve global markets and competition. Following on from this, Cavalcante and Kesting (2011) 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 (Liao, Kickul, and Ma 2009, Tellis, Prabhu, and Chandy 2009, Wei and Lau 2010, Erevelles, Fukawa, and Swayne 2016, Wamba et al. 2017).

Dynamic capabilities and, in particular, its micro-foundations, focus on how an organisation remains competitive in times of uncertainty (Teece 2007, Ambrosini and Bowman 2009). Zollo and Winter (2002) argued that micro-foundations are integral to a business model and to the competitiveness of the firm. Teece (2007) 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 (Helfat and Peteraf 2015). 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

(Kindström, Kowalkowski, and Sandberg 2013, Chesbrough 2010). They do this by determining what technologies to use, business models to apply and market segments to target (Teece 2007). Once an opportunity is seized and the strategic direction has changed, the organisation transforms (Kindström 2010). According to Teece (2007) and Wang and Ahmed (2007), 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 (Teece 2007). In addition, Erevelles, Fukawa, and Swayne (2016), and Opresnik and Taisch (2015) 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' (Teece 2007, 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 3.

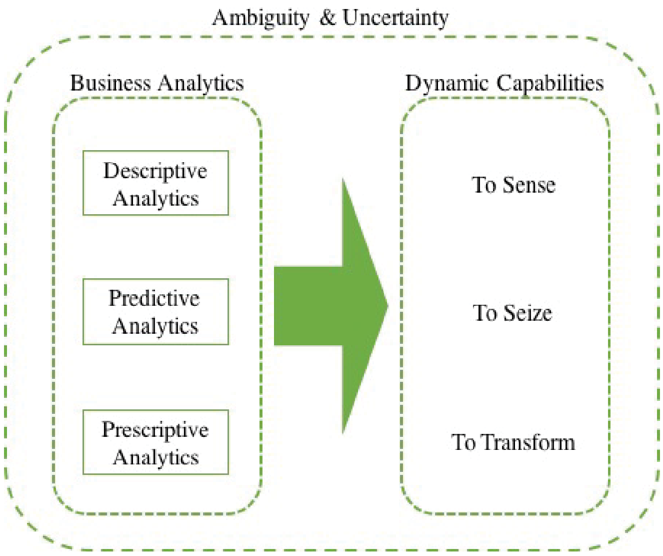


Figure 3: Conceptual framework

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 (Tranfield, Denyer, and Smart 2003) 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 (2002). 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 (Li et al. 2010). 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 (Fainshmidt et al. 2016). As such, papers focusing on, for example, discussions of technical big data implementations (Lu et al. 2014, Homrighausen and McDonald 2016) 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 (Cowie and Lehnert 1996, Randhawa, Wilden, and Hohberger 2016). This method has been applied across a wide range of research (Li and Ramani 2007, Medelyan et al. 2009, Wu and Weld 2010), including business (Yangarber et al. 2000, Saggion et al. 2007), but predominantly in health and biomedical research (Tsai et al. 2007, Coulet et al. 2010, Thompson et al. 2011), 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 (Cowie and Lehnert 1996, Saggion et al. 2007, Srihari et al. 2008, Wu and Weld 2010, Piskorski and Yangarber 2013). Once extracted, the information can be used to develop a graph that shows the relationship between multiple concepts (Li and Ramani

2007). 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 (Sinclair 1991) - called Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003). 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 (Blei, Ng, and Jordan 2003). We used a standard topic modelling tool: the MALLET topic model package (McCallum 2002, Jaworska and Nanda 2016). Subsequently, we expanded this list using Wordnet, which is an NLP resource consisting of a hand coded lexical database for the English language (Miller 1995).

The purpose of applying topic models is extracting terminology from the document collection and organising it in the form of lexicons (Tirunillai and Tellis 2014). 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 (Riloff, Wiebe, and Phillips 2005). Text categorisation entails assigning extracted text to one or more predefined categories to understand relationships between different concepts (Dumais et al. 1998). 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 (Borch and Madsen 2007, Pablo et al. 2007, Teece 2014). 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 (Falagas et al. 2008).

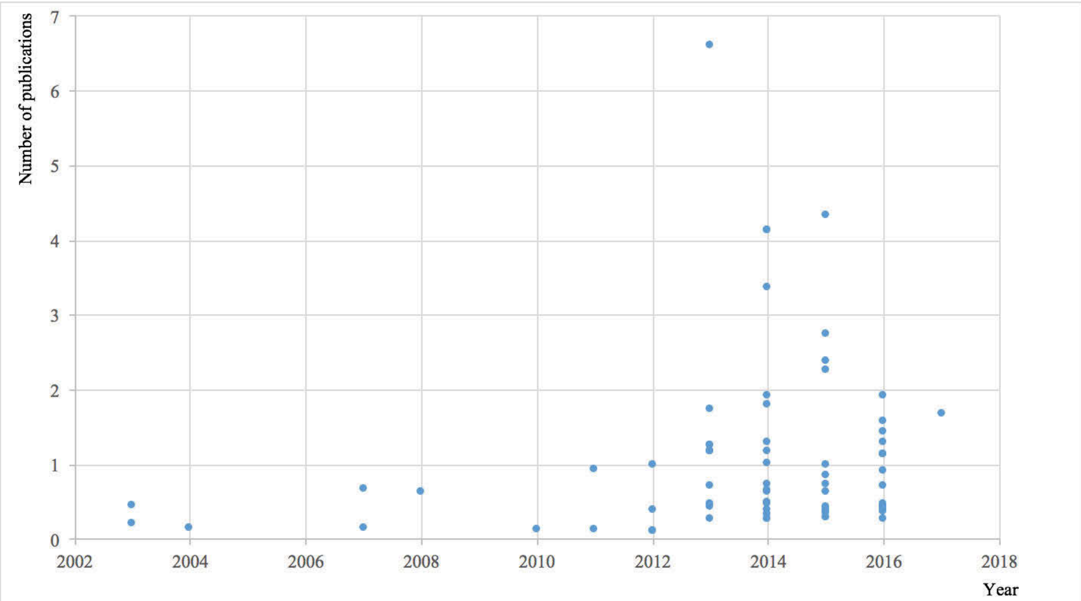
This analysis resulted in the creation of an excel document with a computer-generated summary of each article that contained structured information such as title, journal name and year of publication, as well as industry and country, if available. However, industry and country were too unreliable to 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 (Tony, Merlin, and Julie 2002), new approaches to data extraction (Chan et al. 2016) or the development of a methodological framework for retail forecasting (Ma, Fildes, and Huang 2016), 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 (Carson et al. 2001, Yin 2013). The case study methodology is especially appropriate in new topic areas (Eisenhardt 1989b) and is the best way to understand a certain phenomenon over time (Bromley 1990, Yin 2013).

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 2 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 (Hoon 2013) and understand different applications of big data analytics across different contexts. As Hoon (2013, 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 4 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 4: 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 (Miller 1995). 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 (Sandelowski, Docherty, and Emden 1997). 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 (2013), our objective was to merge the different case specifics using our theoretical framework, understand patterns among the different case studies and contexts (Miles and Huberman 1994), and translate the different concepts and categories from one study to another (Britten et al. 2002, Thomas and Harden 2008), 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 4), which is not surprising given that ‘big data’ has only been around since 2001 (Laney 2001). Figure 4 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 5 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 (Research 2016). Figure 3 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 (IDC 2015). Overall, we are confident that although the data set is relatively small, it covers a relevant sample.

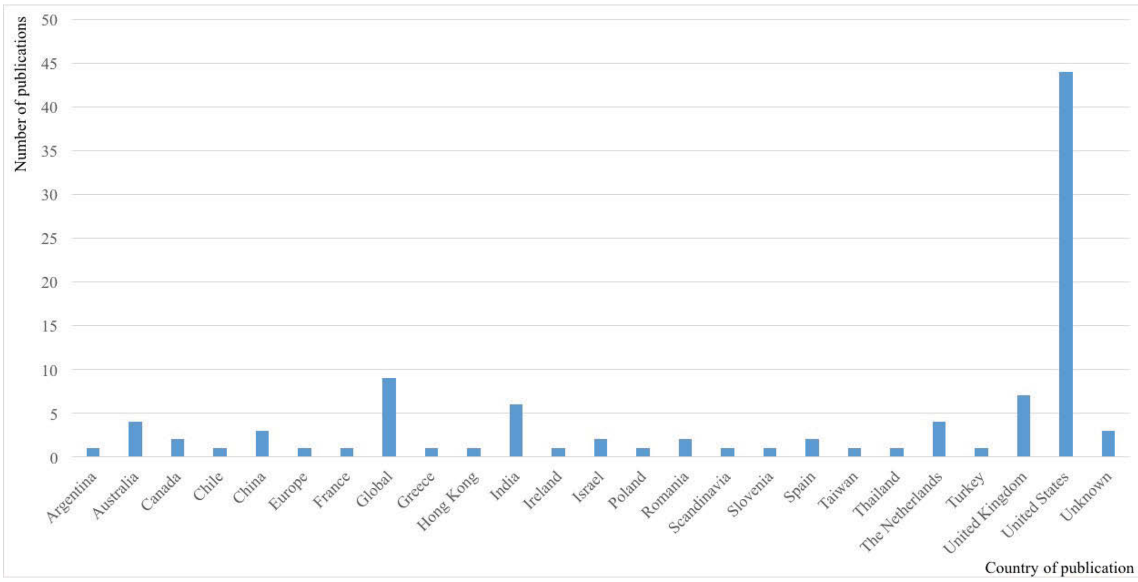


Figure 5: Origin of companies in case studies

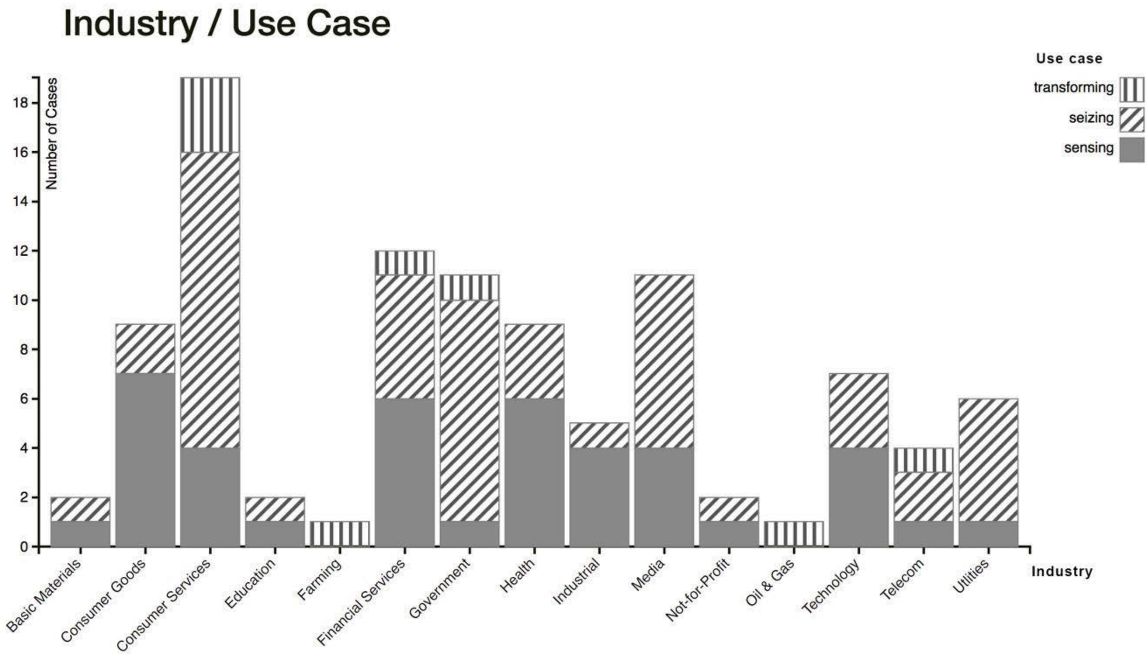


Figure 6: Industries vs use case

Dimension	Descriptive analytics	Predictive analytics	Prescriptive analytics
Sensing	(Overcast et al. 2009, Jun, Park, and Jang 2015, He et al. 2016, Phillips-Wren and Hoskisson 2015, Jones-Farmer, Ezell, and Hazen 2014, Yadav and Soni 2008, Prescott 2014, Jagadish et al. 2014, Russell and Bennett 2015, Sukumar and Ferrell 2013, Höchtl, Parycek, and Schöllhammer 2016, Viitanen and Pirttimaki 2006, McBride 2014, Hawking and Sellitto 2015, Milolidakis, Akoumianakis, and Kimble 2014, O'Leary 2013, He et al. 2015, Moore, Eyestone, and Coddington 2012, Raman 2016, Direction 2012, Gunnarsson et al. 2007, Venkatachari and Chandrasekaran 2016, Verkooij and Spruit 2013, Network_world 2014, Shim et al. 2016, Prasad and Madhavi 2012, He, Zha, and Li 2013, Ghosh 2016, Sinnott 2016, Marine-Roig and Clavé 2015, Mathias, Kessler, and Bhatnagar 2011, Justel-Vázquez 2016, Jetzek, Avital, and Bjorn-Andersen 2014, Tao et al. 2014, Bruns et al. 2014)	(Blackburn et al. 2015, Coussement, Benoit, and Antioco 2015, Park 2014, Tarka and Łobiński 2014, Mookherjee et al. 2016, Sellitto and Hawking 2015, Sun et al. 2014, Chluski and Ziora 2015, Salzillo, Kennedy, and Olinsky 2012, Lozada 2014, Garcia Martinez and Walton 2014, Jin et al. 2016, Janssen 2017, Ciulla et al. 2012, Lewis, Zamith, and Hermida 2013, Cai et al. 2014, Leventhal and Langdell 2013)	(Perugini and Perugini 2014)
Seizing	(Sonka 2016, IM2003_awards 2004, Stojanovic and Kessler 2011, Barnea 2014, Wixom et al. 2008, Paula, Stone, and Foss 2003, Luby and Whysel 2013, Audzeyeva and Hudson 2016, Weiner, Balijepally, and Tanniru 2015, Jermol, Lavrac, and Urbancic 2003, Wixom, Yen, and Relich 2013, Şerbănescu 2012, Şerbănescu and Necşulescu 2012, Foshay and Kuziemsky 2014, Shollo and Galliers 2016, Chongwatpol 2016)	(O'Donoghue et al. 2016, Ferreira, Lee, and Simchi-Levi 2016, Gabel and Tokarski 2014, Vera-Baquero et al. 2015, Miguel and Miller 2015, Wang et al. 2011, Fihn et al. 2014, Osuszek, Stanek, and Twardowski 2016, Dutta and Bose 2015, Bonomo, Durán, and Marenco 2014, Mondare, Douthitt, and Carson 2011, Souza 2014, Liberatore and Wenhong 2010, Doğan, Aşan, and Ayçın 2015, Ashcroft 2012, Bertsimas, Kallus, and Hussain 2016, Amatriain 2013, Halamka 2014, Kalakou, Psaraki-Kalouptsidi, and Moura 2015, Papenfuss et al. 2015, Bekmamedova and Shanks 2014, Fernández-Manzano, Neira, and Clares-Gavilán 2016)	(Pajouh et al. 2013)
Transforming		(Fitzgerald 2016a, Moorthy et al. 2015, McAfee et al. 2012, Fitzgerald 2016b, Nudurupati, Tebboune, and Hardman 2016, Fitzgerald 2016c, Sanders 2016, Galbraith 2014b)	

Table 2: 101 use case articles analysed for meta-synthesis

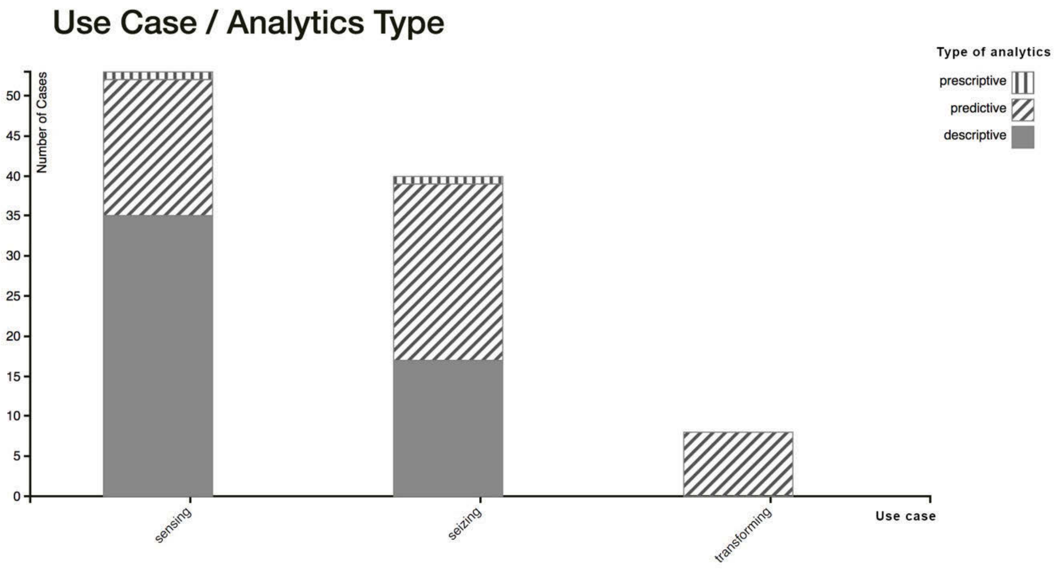
Results

In total, 101 case studies were analysed. Although some case studies discussed multiple companies (He et al. 2016, Milolidakis, Akoumianakis, and Kimble 2014, Raman 2016, He, Zha, and Li 2013, He et al. 2015), 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

<u>Descriptive analytics</u>

Our research revealed that many organisations applying big data analytics use descriptive analytics. As Figure 7 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 (2007) 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 (Teece 2007, Nonaka and Toyama 2007). The micro-foundations Teece (2007) 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 (Teece 2007), as they help to understand its context (Peteraf, Di Stefano, and Verona 2013). The 35 organisations applied descriptive analytics to sense their



environment in a variety of ways.

Figure 7: 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 (Verkooij and Spruit 2013). As the authors, Verkooij and Spruit (2013, 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 (2013, 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 (2007) and Nonaka and Toyama (2007) described as having access to information to discover opportunities. In addition, as Helfat and Peteraf (2015) argued, descriptive analytics enables organisations to scan the environment for change, offering a better understanding of the context of the organisation (Teece 2007).

Apart from context, understanding change among stakeholders is key (Peteraf, Di Stefano, and Verona 2013). A joint venture in the United Kingdom between three magazine publishing companies (McBride 2014) 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 (2007), enables organisations to examine key performance indicators (KPIs) and supplier processes (McBride 2014).

Zollo and Winter (2002) are in favour of making analytics capability an integral part of the business model, which is what Nielsen did to understand consumer behaviour (Prescott 2014). Nielsen, 'the ratings engine for the advertising industry' (Prescott 2014, 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 (Prescott 2014). As Kaisler and Armour (2013) argued, this offers stakeholders insights in a changing environment.

Finally, the city of Barcelona analysed user-generated content to understand tourist profiles (Marine-Roig and Clavé 2015). 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 (Marine-Roig and Clavé 2015). The city employed descriptive analytics to obtain insights on changing tourism behaviour to identify new markets and customer trends (Teece 2007).

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 (Kaisler et al. 2013). Therefore, descriptive analytics offers the antennae required to detect the weak signals that indicate a changing environment (Akkermans and Van Wassenhove 2013, Helfat and Peteraf 2015, Peteraf, Di Stefano, and Verona 2013) and changing customer behaviour (Teece 2007). Descriptive analytics helps to understand the environment of an organisation by providing insights related to the past (Teece 2007). 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’ (Paula, Stone, and Foss 2003, P329). Descriptive analytics was used to segment customer data, integrate these with external data and build a customer cross-sell platform (Paula, Stone, and Foss 2003). As observed by Kindström and Kowalkowski (2013), 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 (Wixom, Yen, and Relich 2013). 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' (Wixom, Yen, and Relich 2013, P114). Using mobile business intelligence, GMobile offered access to information (Nonaka and Toyama 2007, Teece 2007) and visually displayed information, such as bestsellers or sales information, enabling employees to know what markets to target (Teece 2007).

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 (Weiner, Balijepally, and Tanniru 2015). As well as providing access to information, as argued by Nonaka and Toyama (2007), the dashboards helped to mitigate risks and allow users to 'adapt to changes in the organisational culture' (Weiner, Balijepally, and Tanniru 2015, P328). According to Chesbrough (2010) and Kindström and Kowalkowski (2013), such practices foster innovation, resulting in better internal processes.

Finally, a Thai coal-fired power plant employed descriptive analytics (Chongwatpol 2016) 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, and Sandberg (2013) and Kay (2010) argued, allowed them to 'improve the performance of the power plant' (Chongwatpol 2016, 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 (Kindström, Kowalkowski, and Sandberg 2013, Teece 2007, Chesbrough 2010). We encapsulate this in our second proposition:

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

<u>Predictive analytics</u>

Once customer and market trends are understood, a business prepares to seize those opportunities (Teece 2007). This requires decision-making in circumstances of uncertainty and 'investments in development and commercialisation activity' (Teece 2007, P1326) to ensure the correct structures, procedures, designs and incentives are in place (Teece 2007). Teece (2007) identified that, among other factors, this process involved selecting decision-making protocols (Kay 2010), 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 (Teece 2007). These activities anticipate detected unknown unknowns and prepare potential responses. Predictive analytics offers predictions to improve decision-making processes and to understand what opportunities could be seized.

As Figure 7 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' (Fernández-Manzano, Neira, and Clares-Gavilán 2016, P571). In addition, Netflix applied predictive analytics, which, as claimed by Kay (2010) and Kindström, Kowalkowski, and Sandberg (2013), allows for offering product recommendations and facilitating customers' decision-making, on, in Netflix's case, what to watch (Fernández-Manzano, Neira, and Clares-Gavilán 2016). 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' (Dutta and Bose 2015, 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 (Dutta and Bose 2015). The predictive capabilities that RCL implemented can be linked to dynamic capabilities, since predictive analytics enables an organisation to improve its processes (Kindström, Kowalkowski, and Sandberg 2013), make better decisions (Kay 2010) and respond to changes in their environment (Teece 2007).

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 (Teece 2007) and 'to enable informed and insightful decision-making'

(Bekmamedova and Shanks 2014, 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 (Bekmamedova and Shanks 2014). As such, the bank grew its analytical capabilities, which Makadok (2001) and Teece (2007) 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 (2010) and Kindström, Kowalkowski, and Sandberg (2013), 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 (Bertsimas, Kallus, and Hussain 2016). 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 (Coussement, Benoit, and Antioco 2015). As such, predictive analytics can be used to understand customer behaviour (Teece 2007) and the effect on the business.

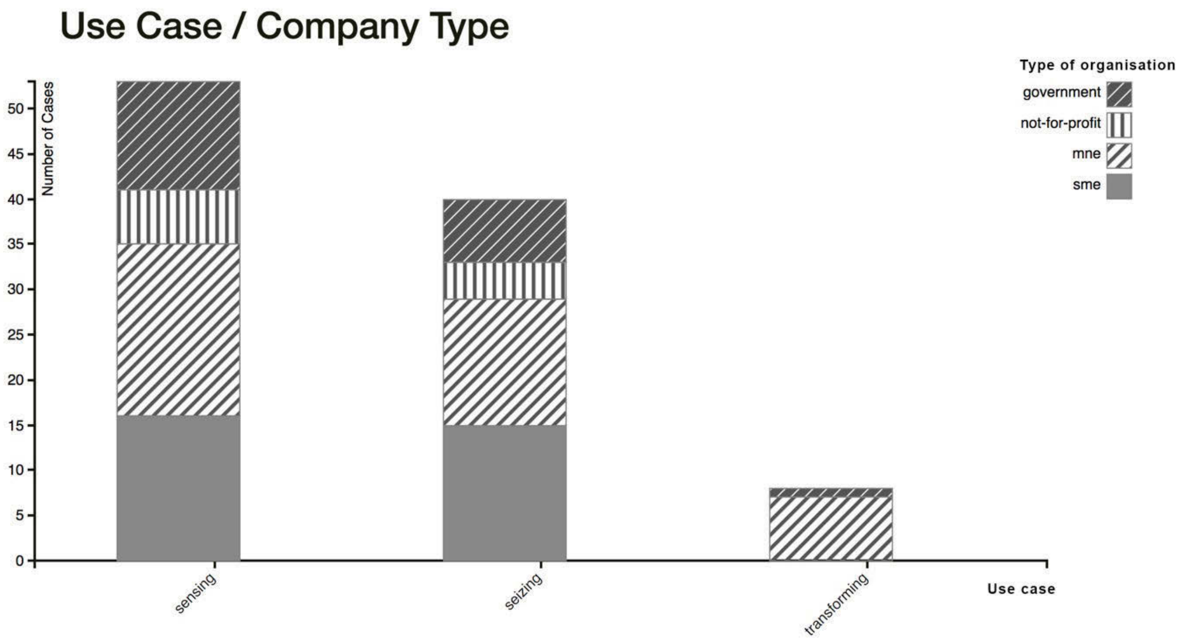
In another example, a Chinese bank was described as generating 'insights for active customers based on their transaction behaviour, using close to 20 terabytes of data' (Sun et al. 2014, P1). The data enabled the bank to identify online customer behaviour; predictive analytics offered insights into customers 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' (Sun et al. 2014, P8), which as Helfat and Peteraf (2015) argue, allows for understanding changing customer behaviour. The next step would be to turn those insights into business rules to improve decision-making (Kay 2010).

Finally, a case study of the Samsung Galaxy i9300 shows that analysing customer reviews using predictive analytics can offer insights into future customer demands (Jin et al. 2016). 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' (Jin et al. 2016, P3033). Therefore, organisations not only use descriptive analytics to sense opportunities; they also turn to predictive analytics to understand their environment (Peteraf, Di Stefano, and Verona 2013). 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 (Teece 2007, Zollo and Winter 2002). However, the key to sustained competitive advantage is the capability to change routines and develop new products and services depending on changing market circumstances (Teece and Pisano 1994, Teece 2007)—that is, to respond to unknown unknowns (Kim and Pennings 2009). According to Teece (2007), this requires a continuous (re)alignment of assets and includes elements that are involved in embracing innovation (Lawson and Samson 2001) and decentralisation, thereby ensuring value-enhancing product development or knowledge management skills that respond to disruptive innovation (Ikeda and Marshall 2016). 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 (Columbus 2016). 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 (Perugini and Perugini 2014). As Figures 7 and 8 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 (Perugini and Perugini 2014) and to improve data-driven decision-making at a steel bar products manufacturer in North America (Pajouh et al. 2013). 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 8: Company type vs analytics type

Figure 9 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.

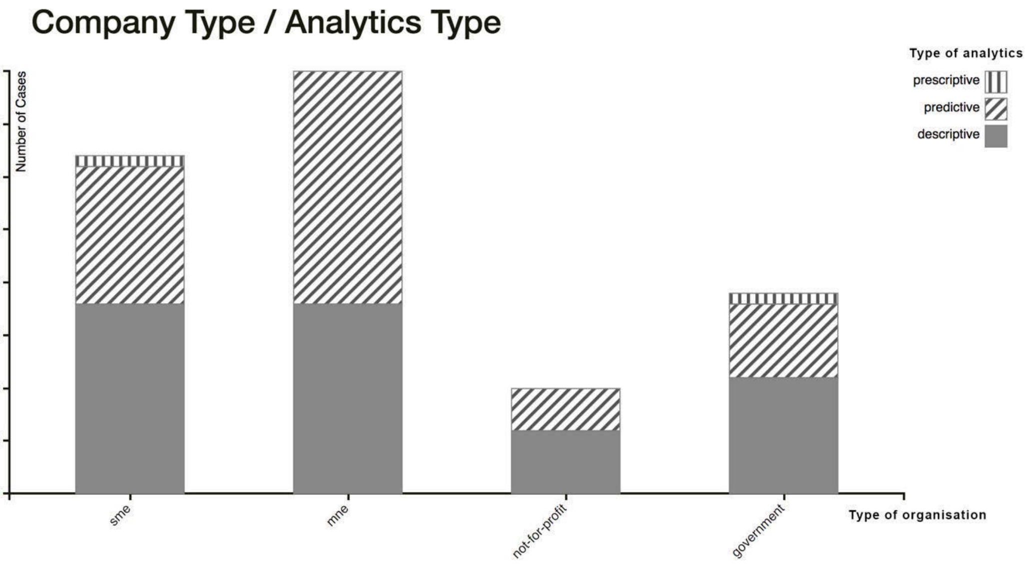


Figure 9: Use case vs company type

As SMEs and not-for-profit organisations generally lag behind in the adoption of big data analytics (European_Commission 2013, Coleman et al. 2016), 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 (Wixom et al. 2008, Hsinchun, Chiang, and Storey 2012, Tanaka 2015, Ouahilal et al. 2016) that overlooks predictive and prescriptive aspects relevant to transforming an organisation (Perugini and Perugini 2014).

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' (Moorthy et al. 2015, P81). This offered the organisation the flexibility to create new, value-enhancing products, which is vital for sustainable growth (Wang and Ahmed 2007). The Bank of England embedded analytics in its policies and actions, which Teece (2007) argued is what should be done. It used more than 1000 structured and unstructured data sets to create new, futureproof policies (Fitzgerald 2016a). The city of Amsterdam used predictive analytics to turn itself into a smart city (Fitzgerald 2016c). In doing so, and in line with Snow and Fjeldstad's (2011) 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 (Fitzgerald 2016c). Finally, the car company Ford used predictive analytics—or, as Ford calls it (Fitzgerald 2016b, 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 (Kindström 2010, Teece 2007, Wang and Ahmed 2007). 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 (George, Haas, and Pentland 2014, Gabel and Tokarski 2014, Pigni, Piccoli, and Watson 2016, Fitzgerald 2016b). As Kaisler and Armour (2013) 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 (De Meyer, Loch, and Pich 2002), 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 (Akkermans and Van Wassenhove 2013). 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 (2012) have argued, if one wants to remain competitive, flexibility in decision-making and flexible organisational processes that can deal with ambiguity and uncertainty (Teece, Peteraf, and Leih 2016, Bennett and Lemoine 2014) are key (Kim and Pennings 2009). 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 (Ruefli 1971, Mintzberg 1989), is exchanged for data-driven decision-making (Galbraith 2014b). 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 (2007). Further, as Snowden and Boone (2007) 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 10, the majority of organisations in our study (44 companies) were MNEs that applied big data analytics in different ways for different use cases.

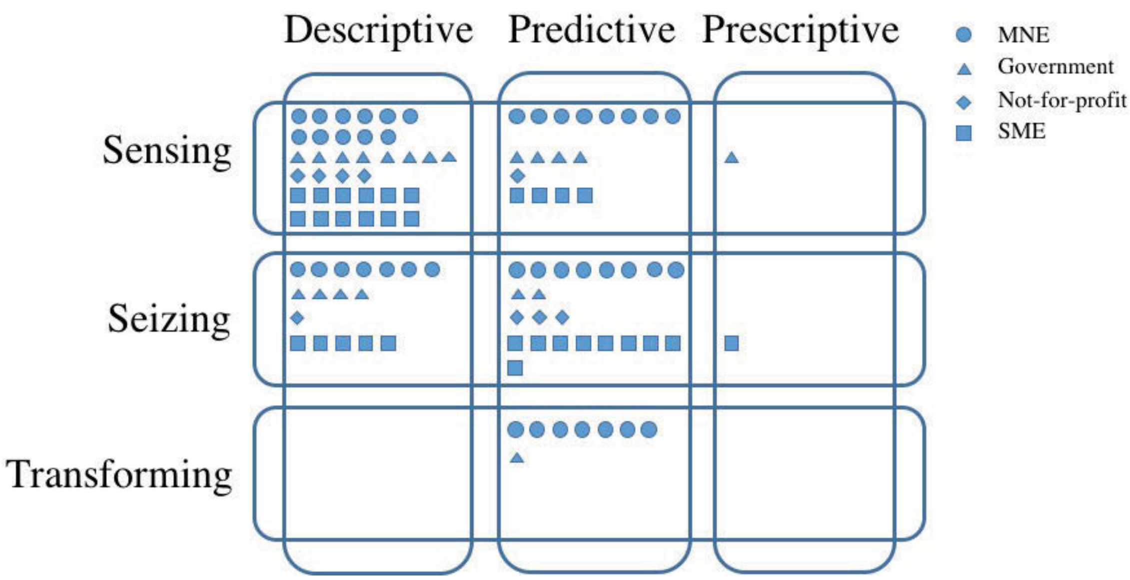


Figure 10: Analytics vs use case vs organisation

Figure 10 shows that MNEs are present in five quadrants. Teece (2014) 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 (2009) and Galbraith (2014a).

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 (Malecki 1987). MNEs operate through a network of market-sensitive self-organising business units (Snow, Miles, and Coleman 1992, Miles et al. 1997) that are vertically or horizontally integrated (Guoqiang 2001). 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 (Merrill 2015, Boyd and Fulk 1996). In addition, regarding knowledge and information sharing, decentralised nodes tend to be open and dynamic across and within different units (Jarvenpaa and Ives 1994). These characteristics enable organisations to rapidly and efficiently respond to changing market demands and uncertain environments (Miles et al. 1997, Powell 2003, Topper and Carley 1999, Baker, Nohria, and Eccles 1992), making them adaptable to their environment, receptive to change and flexible in operation (Merrill 2015, Snow, Miles, and Coleman 1992). This suggests that MNEs are particularly suited to dealing with deep ambiguity and uncertainty (Merrill 2015). 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 (Olavsrud 2015). 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 (March and Scudder 2017). 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 (Morgan 2016), 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 (Khatri and Ng 2000) to decisions based on data (Brown 2008, George, Haas, and Pentland 2014). The ability to analyse data and understand insights derived from data (Davenport, Barth, and Bean 2012) 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 (2007) 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 (2007, 2012), 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 (George, Haas, and Pentland 2014), 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' (Teece 2007), 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 7 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 (Perugini and Perugini 2014). 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 (2007, 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' (Taleb 2007, 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.

4.2 Paper 2: A distributed future: Where blockchain technology meets organisational design and decision-making

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***Keywords**:* Blockchain, decision-making, governance, organisation design, smart contracts, trust.

Abstract

Blockchain technology records and forever maintains data that cannot be changed. It also involves 'smart contracts' and consensus mechanisms that govern processes of automation, as well as the development, evaluation and execution of decisions. Blockchain technology has the potential to transform organisational design due to its decentralised and distributed characteristics. As such, this paper examines decentralised autonomous organisations, which, by design, establish governance and trust among actors, based entirely on autonomous computer software and cryptography. The analysis reveals that current theories of organisation design fail to adequately explain organisational forms that are based on blockchain technology. This conceptual study introduces blockchain technology to organisation design theory and discusses the many challenges organisations are facing once adopted. It proposes a basic framework that explains emerging decentralised and autonomous organisation designs and presents a research agenda for this exciting phenomenon.

Introduction

In 2008, in the midst of the biggest financial crisis in decades (Shiller 2008), a paper was distributed among a small group of cryptography enthusiasts (Reid and Harrigan 2013). Nakamoto (2008), described the concept of a cryptocurrency called bitcoin[i] that resolved the long-standing problem of double spending digital funds (Chaum 1983). Double spending has been the main obstacle to widespread adoption of distributed digital currencies and decentralised digital money. The domain name Bitcoin.org was registered and, in early 2009, the *genesis block*, the first block in a blockchain, was established (Reid and Harrigan 2013). Only ten years later, the impact of Nakamoto's invention on the world's largest organisations, intermediaries and society at large has been described by many as unprecedented (Mattila 2016, Tapscott and Tapscott 2016). Globally, investments in cryptocurrencies and other Blockchain technologies is growing rapidly. In the first three quarters of 2018, blockchain startups and crypto firms have raised US$3.9 billion in venture capital (Diar 2018).

What is Blockchain? Blockchain is the technology behind Bitcoin. It is a database technology with the potential to transform organisations through cryptography, which establishes trust among actors, and smart contracts, which automate decision-making (Tapscott and Tapscott 2016). Blockchain has been coined an invention as important as the internet or limited liability corporations (The_Economist 2015), mostly by eliminating the need for intermediaries and empowering consumers (Mattila 2016) and by changing how industry partners collaborate (Van Rijmenam and Ryan 2019). Shrier, Wu, and Pentland (2016) argue that if Blockchain is applied securely within and across organisations, many of the world's largest problems, such as poverty or identity exclusion, could be solved. Similarly, Tapscott and Tapscott (2016) stated that Blockchain could bring about a better, fairer and more transparent world. However, no academic study has yet investigated how Blockchain affects the design of organisations in general and decision-making in particular. Hence, the objective of this paper is to introduce Blockchain to the field of organisation design and examine how it may bring about new forms of organising or affect relationships among organisations.

We follow Simon's (1973) definitions of *organisation* and *organisation design:* An organisation is a decision-making and information-processing system. Organisation design entails the processes and components that enable an organisation to achieve its goals. Such definition is appropriate in this context given most organisations are heavily involved in information technology (Davenport and Short 1990), and organisation design components, including decision-making, are increasingly determined by information technologies (Clay Dibrell and Miller 2002).

We are interested in how Blockchain changes decision-making within and across organisational boundaries and how it may result in new forms of organisation design. Few studies have focused on the technological aspects of Blockchain technology, such as cryptography (Kosba et al. 2016) and smart contracts (Watanabe et al. 2015). Some studies have focused on Bitcoin (Vigna and Casey 2016), which is one of many applications of blockchain technology. Others have focused on the legal aspects of smart contracts (Savelyev 2017).

We start by providing an overview of how the design of organisations has evolved over time. Considering the historical background is important, as it allows us to understand the role of information technology for the design of organisations and decision-making. It allows us to uncover the role that Blockchain technology may have for organising activities within and across organisations (Swan 2015b). We then discuss the concept of blockchain and show how the design of organisations and decision-making evolves when introducing the ideas of consensus mechanisms and smart contracts.

We discuss key challenges of blockchain technology and offer our perspective of how the application of this technology can result in fundamentally new forms of organisation design. We conclude with formulating a research agenda.

Organisation Design

The theory and practice of organisation design has evolved significantly over the past 100 years. At the beginning of the twentieth century, organisations were mostly seen as closed bureaucracies (Hall 1963). These organisations, involving a strict hierarchy of authority and power, were rational entities and assessed purely based on economic performance criteria. Weber, Gerth, and Mills (1948) called this the 'bureaucratic model', as it captured standardised, authoritative, decision-making procedures, rational discipline and strict separation of planning and execution (Hall 1963). These organisations were authoritative, which means only managers had access to information and were solely responsible for strategic decision-making (Weber, Gerth, and Mills 1948). Trust was based on controlling conformity with the organisational rules (Maroy 2012) and technology. Technology was predominantly manufacturing technology, which had very predictable impacts on how the orgaisation was desigend to perform (Blau et al. 1976, Huber 1990b, Pfeffer and Leblebici 1977).

In the mid–twentieth century, an emerging natural systems theory perspective (Larsson and Bowen 1989) placed humans at the centre of organisations. Now organisations were seen to be made up of individuals with a common goal. Managerial emphasis shifted from controlling individuals to motivating individuals, resulting in additional theoretical perspectives that focused on teamwork, cooperation and motivation (Scott and Davis 2015). Increasingly, employees and technologies were integral parts of organisations (Mills and Turk 1986). Natural systems theory assumes that trust in organisations evolves through teamwork and fostering of informal relationships (Turner 1990), while decision-making is aligned with political processes (Boland Jr and Pondy 1983, Llewellyn 1994). These ideas implicitly defined organisations as closed systems.

With the arrival of open systems theory, the focus of organisation theory shifted once again, now to the interaction of an organisation with its environment. Organisations perceived as open systems had to be flexible. Managers facilitate interaction among stakeholders within the organisation's value network (Scott and Davis 2015, Katz and Kahn 1978). An organisation is a system too, created and activated by input and output (Katz and Kahn 1978). Open systems organisation design is democratic. Employees at all levels participate in accomplishing strategic objectives (Emery 2000) and everyone has access to information resulting in shared decision-making and shared trust among employees (Martins and Terblanche 2003). The appearance of the first wave of advanced information technologies (IT) enabled open system organiation designs (Huber 1990b).

Open systems theory further developed into network systems theory (Burnes 2005). Network systems theory explains how flexible organisations use information technologies to innovate, adapt and connect with actors across time and space (Merrill 2015). Within network organisations, information technologies reduce the breadth, depth and width of an organisation, which supports data-driven decision-making and knowledge-based trust within and across organisations (Kramer and Tyler 1996). A network organisation is adaptable to its environment, receptive to change and flexible in operation, which is necessary in a data-driven world involving frequent exchange of data and knowledge (Merrill 2015). In today's fast-paced business environments, network organisations with increasingly democratic characteristics (Bass and Bass 2009) are very receptive to market and technological developments and able to anticipate disruption (Teece, Pisano, and Shuen 1997b). These organisations have an authoritative to increasingly democratic style of organisation design (Bass and Bass 2009, Weber, Gerth, and Mills 1948, Emery 2000)[ii].

Recently, Snow et al. (2011) proposed collaborative communities as a new form of organisation. Here, organisations use technologies to share knowledge and engage in collaborative relationships and decision-making with industry partners (Lin, Tsai, and Wu 2014). Now, collaborative network organisations turn into platform organisations due to the availability of the second wave of advanced information technologies, which features big data analytics or artificial intelligence, (Romero and Molina 2011). Many new digital platform organisations (Kazan, Tan, and Lim 2014) copy the design of highly successful companies like Uber or Airbnb, increasingly affecting incumbents (Davis 2015). Data-driven platform organisations require a balance between *generativity* and *control* (Yoo et al. 2012) as power and empowerment are shifting (Grossman 2016). The new types also tend to have democratic to delegative styles of organisation design, where self-governed teams no longer report to management (Burnes 2005).

Robertson (2015) also added the holacracy, which is especially relevant for organisations facing rapid changes. The holacracy design revolves around advanced information technology enabling dispersed teams to work together within an organisation, without formal management making the decisions (Robertson 2015).

We argue that future forms of organisation design will move to a delegative style of organisational design and decision-making as the availability of information technology within the organisation enables self-governed actors to create value. The emergence of Blockchain in general, and smart contracts in particular, are important drivers for this development. As we will see, blockchain technology contributes to creating value using cryptography, consensus mechanisms and smart contracts (Kane 2016) through a network of peer-to-peer actors distributed across the globe, collaborating effortlessly and in real-time to create value for all actors in the network (Carroll and Bellotti 2015). Within this 'Internet of Value' (Tapscott and Tapscott 2016) (i) miners create value by validating transactions; (ii) smart contracts create value by executing certain tasks automatically; (ii) organisations create value through increased efficiencies and reduced costs using the distributed ledger; and (iii) consumers create value through reduced prices and more spare time, overall, resulting in increased value creation for society as a whole (Tapscott and Tapscott 2016). When implemented to the extreme, these technological features can result in new forms of organisation design (Buterin 2014, Swan 2015b, Forte, Romano, and Schmid 2015, Tapscott and Tapscott 2016), affecting organisations and inter-organisational relations as well as changing strategic management practices due to automated decision-making (Swan 2015b, Davidson, De Filippi, and Potts 2016). This does not mean that existing organisation designs cease to exist,. On the contrary, organisations that do not use distributed ledger technology are not be affected. However, those organisations that do, will change significantly.

The currently most revolutionary organisation design is that of the decentralised autonomous organisation (DAO) (Buterin 2014), which uses distributed ledger technology and smart contracts to establish governance without management or employees, and is run completely by computer code (Garrod 2016). DAOs are complex mechanisms that operate autonomously and conform to compliance automatically (Swan 2015b).

The DAO is an extreme form of organisation design, removing any human actors from the equation and having technology itself determine how to organise activity. Eventually, these new organisations may change society by enabling peer-to-peer collaboration and removing the need for intermediaries (Buterin 2014, Swan 2015b, Forte, Romano, and Schmid 2015, Tapscott and Tapscott 2016). While this may seem (too) radical for some, the first DAO was already developed in 2016 (although it subsequently failed) (DuPont 2017). Since, multiple further attempts have been made to create a successful DAO (Chohan 2017). It is very likely for more Decentralised Autonomous Organisations to emerge in the (near) future. Before we examine the concept of a decentralised and autonomous organisation in more detail, we first need to discuss blockchain technology.

Blockchain: Immutable, Verifiable and Traceable

Blockchain is known for being the technology behind Bitcoin; however, the idea of an immutable ever-growing ledger can actually be traced back several decades. In the 1980s and 1990s, a group called the Cypherpunks discussed the need and possibilities of a digital currency that was anonymous, based on cryptography and applied various concepts of today's blockchain technology (Chaum 1992, 1985, Massias, Avila, and Quisquater 1999, Szabo 1994). The popularity of Bitcoin in recent years has brought Blockchain into the public domain.

A blockchain is a shared public or private ledger that describes a single version of the truth of ownership (Forte, Romano, and Schmid 2015, Yermack 2017, Norta 2015a). It is a distributed ledger that uses database technology to record and indefinitely maintain an ever-growing list of data records (Lemieux and Lomas 2016, Chaum 1985, Nakamoto 2008) that cannot be tampered with and are immutable, verifiable and traceable (Umeh 2016, Mattila 2016, Lemieux and Lomas 2016, Van Rijmenam and Ryan 2019). The true technical innovation of Nakamoto (2008) was that this became possible in a public ledger, without reliance on a closed membership (i.e., anyone can join the distributed network and participate). At first, these data records were bitcoin transactions; however, applications have now moved to any type of transaction, across any industry. Blockchains can serve as a record keeper for societies, including registration of any type of document or property (Swan 2015b). Data records are stored chronologically in *blocks* that are *chained* together cryptographically. Every node (i.e. a computer) in the network has a copy of the blockchain and, for a transaction to be added to a blockchain, there has to be a consensus among the nodes in the network.

There are different types of blockchains. The type of blockchain selected determines how actors in the network interact with each other. There are public and private blockchains as well as permissioned and permissionless blockchains, each with different characteristics, rules and actors. The most well-known public and permissionless blockchain is the bitcoin blockchain. Anyone can join a public permissionless blockchain by connecting a computer to the network, downloading the blockchain and starting to process transactions. For actors who want to join the network, there is no approval required nor a previous relationship with the ledger. No single actor controls or owns the blockchain and anyone can contribute at any time. Trust within the system is created through game-theoretical incentives and cryptography. Conversely, private blockchains do not require these artificial incentives since all actors in the network are known to each other. A private blockchain is by definition a permissioned blockchain. New actors have to be approved by existing participants in the network, which enables more flexibility and efficiency in validating transactions (Mattila 2016). Private blockchains are generally used by organisations that like to keep a shared ledger for settlement of transactions, such as the financial services industry. Private blockchains are owned and operated by a group of organisations and transactions are visible only to members of the network (Shrier, Wu, and Pentland 2016). An example of a private blockchain is the Utility Settlement Coin (USC) developed by 11 of the biggest global banks, led by Swiss bank UBS (Kelly 2016). The USC is the digital counterpart of each of the major currencies backed by central banks. The objective is to develop a settlement system that processes transactions in (near) real-time, rather than days. The aim of the project is to enable global banks to conduct various transactions with each other using collateralised assets on a custom-built blockchain and to make financial markets more efficient (Arnold 2017). Another example is Australia Post, which has released plans for developing a blockchain-based e-voting system for the state of Victoria, Australia (Palmer 2016). Finally, Walmart is employing IBM's commercial version of the Hyperledger blockchain to ensure the provenance of some of their perishable products such as mangos and bananas and track these products throughout the food chain (Yiannas 2018). Recently, hybrid blockchains have started to appear. These are public and permissioned, which means that everyone can join the network, but they have to be approved first, for example by completing a verification.

The type of blockchain that an organisation could adopt depends on the objective of the organisation and the type of transactions that need to be stored on a blockchain. Some transactions cannot be visible to the general public, such as financial transactions. Other transactions, such as ownership of (digital) goods, benefit from a public blockchain (Pilkington 2016). Every distributed ledger technology makes use of cryptographic primitives, such as public key infrastructure (PKI) and hash algorithms, time stamps and consensus mechanisms. As a result, data on a distributed ledger technology becomes immutable, verifiable and traceable, which has the potential to significantly change decision-making within and across organisations. For an explanation on PKI and time stamps, we refer to the endnotes[iii] and we will next discuss how decision-making could be changed due to consensus mechanisms and smart contracts.

Changes in decision-making

Organisations are part of complex interacting environments. Selznick (1948) defined organisations as adaptive social structures that react to internal and external influences in which systems of relationships define the availability of scarce resources that can be manipulated. In addition, according to Baum and Singh (1994), organisations live in dynamic environments where multiple internal and external actors influence the organisation and its likelihood for success. As we have seen, over the years decision-making moved for an authoritative process (Weber, Gerth, and Mills 1948) to collaborative decision-making (Lin, Tsai, and Wu 2014, Snow et al. 2011) and even delegative decision-making (Robertson 2015). With the arrival of distributed ledger technology in general and consensus mechanisms and smart contracts in particular, the concept of decision-making will again change drastically:

The consensus mechanism

Consensus decision-making has been used by humans for many years (Johansen 1995). Although it began as a concept applied to politics and societies, it has become an important part of computer science (Olfati-Saber, Fax, and Murray 2007). Consensus algorithms ensure that connected machines can collaborate independently without the need to trust each other and can continue working even if some members of the network fail (Olfati-Saber, Fax, and Murray 2007, Seibold and Samman 2016). There are a multitude of consensus algorithms that take different approaches to authenticating and validating values and transactions on a blockchain. Consensus mechanisms are key to any blockchain; they remove the need for trust between parties and, as a result, decisions can be made, implemented and evaluated without the need for a central authority (Davidson, De Filippi, and Potts 2016, Seibold and Samman 2016, Swan 2015b). The result is intermediary-free transactions and decision-making, whether it is human-to-human, human-to-machine or machine-to-machine (Swan 2015b).

As there is no trusted central authority, consensus is vital to blockchains. Actors in the network have to agree upon the rules that govern the blockchain and how these rules must be applied before a blockchain is deployed. The nodes in the network execute an agreed-upon algorithm and a pre-defined majority must agree on the outcome. Consensus algorithms use cryptography to validate transactions (and thus decisions) and, at the moment of writing,[iv] the two most common consensus algorithms are Proof of Work (PoW)[v] and Practical Byzantine Fault Tolerance (PBFT). PoW is commonly used in permissionless blockchains, while PBFT is used in permissioned blockchains. New consensus algorithms are being developed constantly (Cachin and Vukolić 2017), including Proof of Stake (PoS),[vi] an experimental algorithm that is only used in a few blockchains and is not yet mature. A consensus algorithm solves the long-standing problem of double spending related to cryptocurrencies. Double spending refers to actors who want to cheat the system by spending the same crypto coin more than once. With fiat money, this problem is solved through the usage of a central authority—a bank. In a decentralised system, without a central authority, it can be solved by consensus. To understand the issue, Lamport, Shostak, and Pease (1982) proposed 'The Byzantine Generals' Problem', a thought experiment about a group of generals who each command a different part of the Byzantine army and need to agree upon a plan to attack and conquer an enemy city. The generals can communicate only via messenger and at least one of them is a traitor. The question is: how many traitors can the army have and still function as one force? Every consensus algorithm is a solution to the Byzantine Generals' Problem. The first algorithm to resolve the problem was the PBFT (Castro and Liskov 1999). Many PBFT algorithms were developed before Bitcoin was introduced. PBFT algorithms can be applied in decentralised, permissioned networks, meaning that a central aspect to PBFT algorithms is that membership—which has to be approved by a centralised authority—is required. The PoW algorithm solved the problem of membership (Seibold and Samman 2016, Nakamoto 2008). This consensus algorithm operates in a decentralised network, without a central authority; however, it assumes that the majority of actors are 'honest' and reduces the risk of dishonest actors to improve decision-making. Thanks to consensus mechanisms, decision-making can now be done decentralised without a central authority. With the arrival of smart contracts, decision-making can also be automated.

Smart contracts

Data on a blockchain is immutable, verifiable and traceable and since trust among actors collaborating on a blockchain is ensured by cryptography, intermediary-free transactions and decisions are possible. This removes the need for trusted centralised third parties, who generally take a commission for verifying transactions (Swan 2015b)[vii]. Removing intermediaries completely changes how actors interact with each other and how decisions are made, implemented and evaluated (Christidis and Devetsikiotis 2016). Bitcoin transactions are still the most well-known transactions recorded on a blockchain. However, other transactions related to any other currency, financial contracts or hard and soft assets can also be recorded (Swan 2015b). In fact, any type of transaction, whether related to digital or physical goods, can be recorded on a blockchain, including land registry (Garrod 2016); tracking of goods through a supply chain (Pilkington 2016); internet of things (IoT) devices (Zhang and Wen 2016); identity, reputation or natural resources (O'Dwyer 2015); and peer-to-peer exchanges, such as taxi rides or home sharing (Tapscott and Tapscott 2016). Ownership of physical products can also be transferred and stored on a blockchain when owners of physical products, such as art, sell their assets by transferring a private key attached to that asset (Swan 2015b). When this is done automatically using smart contracts, it is called smart property (Swan 2015b). Smart contracts are a special branch of transactions that can be stored on a blockchain (Buterin 2014). It has been proposed that smart contracts will have a major effect on organisation design and will enable automation of decision-making processes (Buterin 2014, Swan 2015b, Tapscott and Tapscott 2016).

The term smart contract was first coined by Szabo (1994) as 'a computerized protocol that executes the terms of a contract'. It can be seen as a traditional agreement that is defined and executed by code, automatically and without discretion (Swan 2015b). Smart contracts are analogous to scripts for processing transactions and/or decisions run on a blockchain; they are 'the killer application for the cryptocurrency world' (Crosby et al. 2016, 13). Smart contracts can be seen as 'if this, then that' statements—albeit significantly more complicated. They are software programs that execute certain transactions or decisions that are agreed upon by two or more actors (Morini 2016). They are created by choosing events or preconditions and by providing information about what needs to happen when those preconditions are met. The protocol is then recorded on a blockchain and, once deployed, cannot be altered and will always execute once the preconditions are met (Luu et al. 2016).

Smart contracts have three distinctive characteristics: they are *autonomous* (after deployment on a blockchain they cannot be altered), *self-sufficient* (they can accumulate and spend value over time) and *decentralised* (they are distributed across multiple nodes within a network) (Forte, Romano, and Schmid 2015, Swan 2015b). Smart contracts can automate decision-making within a network. However, actors involved with creating them have to ensure that the parameters involved with a decision are correct; once a smart contract is on a blockchain, it is final and cannot be changed (i.e., they become immutable, verifiable and traceable). Although, if allowed in the original code, certain parameters can be altered to incorporate changes in the environment.

The financial services industry is rapidly implementing smart contracts in their infrastructure (Cant 2016). Smart contracts can be used to automatically verify customer information against known centralised information, such as during the required Know Your Customer check. In addition, smart contracts can improve the complex mortgage process, resulting in lower processing fees once external partners such as credit scoring companies or land registry offices obtain access to the same blockchain. Finally, insurance companies can apply smart contracts to improve claims processing, as smart contracts can automatically pay out once a claim is handled by a registered vendor. As these examples demonstrate, smart contracts enable automated decision-making among different stakeholders within an industry, resulting in more efficiently collaboration (Cant 2016).

Smart contracts not only have an effect on contract law but also, more broadly, on social contracts within society and organisations, since they minimise the need for trust by taking out human judgement (Swan 2015b). Although smart contracts remove the need for developing, implementing or evaluating decisions made by management or employees once the contracts are deployed on a blockchain, it still involves manual decision-making in defining the parameters of the contract. When multiple smart contracts are combined together with artificial intelligence and big data analytics, it will result in a 'fundamentally new paradigm for organising activity' (Swan 2015b, 27) thanks to automated (strategic) decision-making (Mattila 2016). However, blockchain is still a nascent technology and, hence, there are several challenges that need to be solved before it can become mainstream.

Challenges of Blockchain

When organisations adopt new technologies, the context of that technology plays an important role (Orlikowski 2009). How people deal with the material properties of a new technology is informed by their previous experience of using or not using similar technologies in the past (Leonardi and Barley 2010). Since blockchain is still a nascent technology, how organisations adopt this technology also depends on how existing challenges related to this technology are resolved. These challenges affect how organisations apply blockchain and smart contracts and whether organisation design and decision-making capabilities within organisations will or can change at short notice.

The first challenge is the technical scalability of Blockchain, which is, at least for public blockchains, a hurdle that could limit their adoption. For example, the bitcoin blockchain is currently growing at 1 MB per block, every ten minutes (Croman et al. 2016) and currently has a size of 190 Gigabyte.[viii] Actors in the network that validate transactions are required to download the entire bitcoin blockchain (Antonopoulos 2014), which could pose a problem in the long run. In 2017, this scalability challenge resulted in a group of miners deciding to hard fork and create a new cryptocurrency, Bitcoin Cash, that enables 8 MB blocks. Scalability is less of a problem for private blockchains, such as Hyperledger, since the nodes in the network have a direct interest in processing transactions (Davidson, De Filippi, and Potts 2016), meaning that the computational power that is required to validate blocks is less of an issue. If transactions cannot be verified in real-time or within a short timeframe, it affects the technical adoption of a blockchain, as rapid decisions are often required, especially in today’s high-velocity environments (Eisenhardt 1989b).

The second challenge is related to the transaction speed of a blockchain. In 2018, the bitcoin blockchain is capable of processing seven transactions per second, while the Ethereum blockchain could, theoretically, process eight transactions per second.[ix] Compared with VISA, which routinely handles 2000 transactions per second—but peaked at 56,000 transactions per second (Croman et al. 2016)—Blockchain will take time to reach these levels; meanwhile, new distributed ledger technologies are being developed that offer thousands of transactions per second.

The third challenge involves level of decentralisation with the bitcoin blockchain. Although this does not apply to all distributed ledger technologies, it is important to point out. The power of Bitcoin lies in the fact that it was designed as decentralised and not one centralised stakeholder could control the network (Nakamoto 2008). Unfortunately, today a majority of Bitcoin's collective hash rate, i.e. the mining power, is controlled by mining pools[x]. This centralisation of validating transactions is a logical consequence of how the bitcoin protocol was developed, as it rewards economies of scale. This does not have to be a problem, as long as the mining pools can be trusted and have an incentive to do the right thing.

The fourth challenge, from an organisation design perspective, is the lack of talent to build decentralised applications. Educating employees to work with blockchain takes time; however, it is not yet taught at many educational institutions. As is the case with all new technologies, organisations and academia need to work together to ensure the correct curriculum is introduced (Bailey and Stefaniak 1999). There are already hundreds of blockchain startups, all trying to attract the same limited talent. Organisations are faced with a talent pool that is expanding more slowly than demand is growing (Barr and Tessler 1998). Therefore, organisations that want to embrace Blockchain need to have deep pockets to pay for expert salaries or rely on employees that have only just started learning this new technology (Barr and Tessler 1998).

The fifth challenge is that a decentralised ecosystem surrounding blockchain and supporting distributed products and services is needed. This includes decentralised cloud storage (currently being developed by companies such as Ethereum and the InterPlanetary File System (IFPS)), decentralised archiving, decentralised communication and a decentralised Domain Name Servers (DNS) (Swan 2015b).

Most of these technologies are not yet fully developed, resulting in significant risks for anyone that wants to get involved with Blockchain and develop completely decentralised and autonomous organisations.

The sixth challenge is related to the energy consumption of decentralised networks. Although there are a variety of consensus mechanisms, the Proof of Work consensus mechanism is still the most used mechanism. Proof of Work requires solving complicated puzzles, which uses vast amounts of energy (Van Rijmenam and Ryan 2019). It is estimated that the Proof of Work consensus mechanism in the bitcoin blockchain will use the equivalent of the energy consumption of Denmark by 2020 (Deetman 2016). However, new blockchains might use different consensus mechanisms, which require significantly less energy.

There are also challenges related to data on a blockchain. Resilience and irreversibility are two key attributes of blockchains; once data or transactions are appended and accepted by the network, they can no longer be changed (Umeh 2016). However, only authenticity can be ensured through a blockchain, not reliability and accuracy. If bad data are offered in the right way, they will end up on a blockchain; likewise, if a document contains false information but is offered in the right way, it will end up on a blockchain (Condos, Sorrell, and Donegan 2016). Theoretically, data on a blockchain will be there indefinitely. However, the cryptography used today might not be secure in the (near) future with the development of quantum computing (Swan 2015b). Therefore, data governance will only increase in importance within organisations that adopt Blockchain. Poor execution of smart contracts and, hence, poor automated decision-making, can result in tremendous problems.

Finally, although Blockchain reduces costs and increases efficiencies due to a shared ledger and smart contracts, lack of standards could cause a counter effect.

Standards are important for networks that deal with information systems (Monteiro and Hanseth 1996) and can also help to align an industry (Reutzel 2016). However, obtaining global industry standards for new information technology is difficult and it could take some time before organisations have a shared global blockchain standard, which the International Organization for Standardization is working on.

Blockchain is a promising technology; however, it faces numerous challenges that could affect its adoption across organisations. Scalability and the lack of speed, talent and standards could slow down both the adoption of the technology and the development of new blockchain applications, negatively affecting the development of new organisational forms such as DAOs. Yet, despite these challenges, there have been dozens of new applications in almost every industry that apply distributed ledger technologies (Swan 2015b, Pilkington 2016).

Changing Organisation Design

Smart contracts can enable a wide variety of applications, not only those related to financial markets and/or 'self-enforcing autonomous governance applications' (Luu et al. 2016, 1). Therefore, the possibilities of Blockchain are nearly endless; it can enable organisations to create new, distributed, products and services that will result in efficiency gains in organisations (Mattila 2016) and increasingly automated decision-making capabilities. Such Blockchain-enabled products and services are commonly referred to as decentralised applications (DApps).

A DApp has at least two distinctive features (Swan 2015b): 1) any changes to the protocol of the DApp have to be approved by consensus and 2) the application has to use a cryptographic token, or cryptocurrency, which is generated according to a set algorithm. Hence, consensus mechanisms and cryptographic primitives result in a new form of organisation design: the *decentralised organisation*. An organisation built upon DApps is a decentralised organisation in which decisions are made using consensus by decentralised actors; trust among actors is created cryptographically; and governance is embedded within the code, bringing the code to the data (Shrier, Wu, and Pentland 2016). Decentralised applications do not require a centralised authority for maintenance, as the database is stored on thousands or millions of decentralised computers. Its decentralised infrastructure ensures that a single case of mismanagement resulting in a point of failure does not affect the entire network (Shrier, Wu, and Pentland 2016). In addition, due to the trustless system based on cryptography, the use of blockchain and smart contracts enable an organisation to control and reduce opportunism (Davidson, De Filippi, and Potts 2016), thereby directly influencing the behaviour of the firm (Morini 2016).

Although Blockchain removes the need for trust in the absence of a centralised governing body, any organisation developing DApps requires a strong focus on data governance. As mentioned, only data authenticity can be ensured; reliability and accuracy cannot be guaranteed. Laws and regulations can be programmed into a blockchain itself, so that they are enforced automatically, which makes governance easier, or even automatic. Hence, the distributed ledger can act as legal evidence for data, increasing the importance of data ownership, data transparency and auditability (Zyskind and Nathan 2015). Smart contracts and immutable records on a blockchain, combined with big data and artificial intelligence, enable a second new form of organisation design: *autonomous organisations*. Autonomous organisations have automated decision-making capabilities. Already, traditional organisations can incorporate different aspects of *decentralised* and *autonomous* organisation design by incorporating blockchain for various applications; however, when these two new forms of organisation design are combined, they could become DAOs.

A DAO is a combination of smart contracts linked together, possibly connected to IoT devices, big data analytics and artificial intelligence. Although it is run by immutable code under the sole control of a set of irreversible business rules (Forte, Romano, and Schmid 2015) this does not mean it cannot respond to a changing environment. Smart contracts might be reactive but, with big data analytics, a DAO can be as flexible as any traditional organisation if insights from big data analytics are used as input for smart contracts. A DAO will have different actors from today's organisations, it will require extensive data governance processes ensuring data reliability and accuracy, and it will result in a fundamentally new organisational structure (Swan 2015b, Wright and De Filippi 2015, Norta, Othman, and Taveter 2015, Norta 2015b). A DAO is a self-organising framework that uses automated decision-making based on consensus generated through actors interacting without the need to trust one another. Within a DAO, there is no traditional organisational hierarchy, as hierarchy is determined by ownership, trust and merit. This change in organisational structure alters the power balance. In traditional organisations, power is distributed either by hierarchy or knowledge and often these are related; the higher you are in the hierarchy, the more information you have and the more power you have within the organisation (Foucault 1977). Within a DAO, this works differently. Power is determined by the number of tokens an actor owns, an actor's trust level and the actor's achieved merits. This shifts the power balance within an organisation from a hierarchical structure to a distributed structure (Kosten 2015).

In its simplest form, a DAO is just immutable computer code; one or more smart contracts linked together and deployed on a blockchain, encouraging actors to self-organise. The code defines governance (i.e., the rules that are implemented within the smart contracts) within the DAO. DAOs can operate as traditional organisations; however, they do this autonomously thanks to interconnected smart contracts. DAOs can order products and services, have customers and suppliers, make a profit or loss, and pay taxes as well as dividends. DAOs have the same activities as traditional organisations: they need to make money; they have costs, customers, shareholders and even employees (although these are independent contractors); they offer a product or service; and they are subject to regulatory requirements (although, being a distributed company, this can become difficult as regulations and regulatory requirements can be contradictory across countries). Therefore, governance is important when developing a DAO and a governance structure has to be incorporated within the DAO (i.e., within the code). In addition, developers need to ensure that the code of the DAO not only works, but also works correctly and indefinitely because, once deployed on a blockchain, it becomes irreversible. Lack of governance or quality assurance can have major consequences. Therefore, actors that wish to establish a DAO must ensure that the right governance structure is implemented within the code and that the code works correctly to guarantee that the DAO can operate properly once deployed.

Within a DAO there is no management, only decision-making capabilities that are executed by the code, which is distributed across thousands of computers. Hence, decision-making shifts from centralised by management to decentralised by code. Therefore, for decentralised and autonomous organisations to be successful, a decentralised decision-making and governance framework is required (Norta 2015b, Yermack 2017, Norta 2016). This can be achieved through cryptography and consensus mechanisms (Wright and De Filippi 2015). In addition, game theory allows actors to operate independently and interact with each other using smart contracts

(Forte, Romano, and Schmid 2015, Lewenberg, Sompolinsky, and Zohar 2015, Norta 2016). The technology provides the chance of removing inadequacies often associated with traditional organisations, such as opportunism, fraud, money laundering or corruption, as any transaction will be immutable, verifiable and traceable (Davidson, De Filippi, and Potts 2016, Morini 2016).

As companies adopt fundamentally new forms of organisation design, automate decision-making and rely more on the crowd and the code than any other type of organisation, it potentially requires scholars to adapt existing organisation design theories. For example, within Cyert and March's (1963) behavioural theory of the firm, goals for the organisation are set by top management and are implemented at different levels. However, within a DAO, these goals are set by the shareholders building the DAO before it is deployed on a blockchain and are executed automatically by smart contracts. The outcome of decisions is determined by the parameters incorporated within the smart contract, such as minimum availability of funds within the firm or minimum price levels for certain transactions[xi]. New forms of organisation design based on cryptography, consensus mechanisms and smart contracts will change how actors within the organisational network interact with each other and how decisions are made (Swan 2015b). Even if an organisation only moves partially to a DAO design, the use of blockchain and smart contracts affects how actors interact with each other (Fairfield 2014) and changes decision-making capabilities, since blockchain reduces opportunism within networks (Davidson, De Filippi, and Potts 2016) and automates decision-making. Further, as a result of sharing the same database across time and space, industry partners can become more intensely connected with each other, which increases the number of actors and interactions within the network, resulting in collaborative community designs.

Therefore, we argue that blockchain and smart contracts will result in two new forms of organisation design being included in the discourse on organisation design: decentralised and autonomous. These forms differ from past discussions on decentralised and autonomous organisations (see Table 1), in which decentralisation and autonomy were achieved by re-organising human interactions and decision-making (Ruefli 1971, Dewar and Dutton 1986, Mintzberg 1989). The existing literature views decentralised and autonomous organisations as organisations in which trust is created by experience and forging relationships, decision-making is based on expertise and seniority, and governance is established by a board of directors (Ruefli 1971, Dewar and Dutton 1986, Mintzberg 1989, Pacanowsky 1988, Strikwerda 2003). We defined *decentralised* as an organisation design that uses consensus mechanisms and cryptographic primitives to ensure trust among actors (Davidson, De Filippi, and Potts 2016) who are decentralised across time and space. An *autonomous organisation* is an organisation that is run completely by immutable code, in which decision-making is automated using smart contracts (Swan 2015b, Davidson, De Filippi, and Potts 2016) and governance is embedded in the code (Shrier, Wu, and Pentland 2016). A decentralised organisation does not have to be autonomous, but an autonomous organisation has to be decentralised.

	Traditional Decentralised Organisations	**New Decentralised Autonomous Organisations**
Trust	Experience and relationships	Cryptography
Decision-making	Expertise and seniority	Automatically using smart contracts
Governance	Established by board of directors	Embedded in the code

Table 3: Traditional and New Decentralised Organisations

Decentralised and autonomous organisations rely heavily on a delegative style enabled by extensive applications of information technology. This brings us to our conceptual framework, which shows the two new forms of organisation design we would like to add to the discourse on organisation design. We argue that the more an organisation applies distributed ledger technology, the more it moves to a delegative style and the more decisions are delegated or even automated and trust (within and among organisations) is replaced by mathematics. When that occurs, actors' interactions will be guided purely by autonomous software algorithms (Swan 2015b, Garrod 2016, Forte, Romano, and Schmid 2015) and organisations will move from "social entities" to "artificial entities" where no longer individuals represent the most vital element of an organisation, but code does.

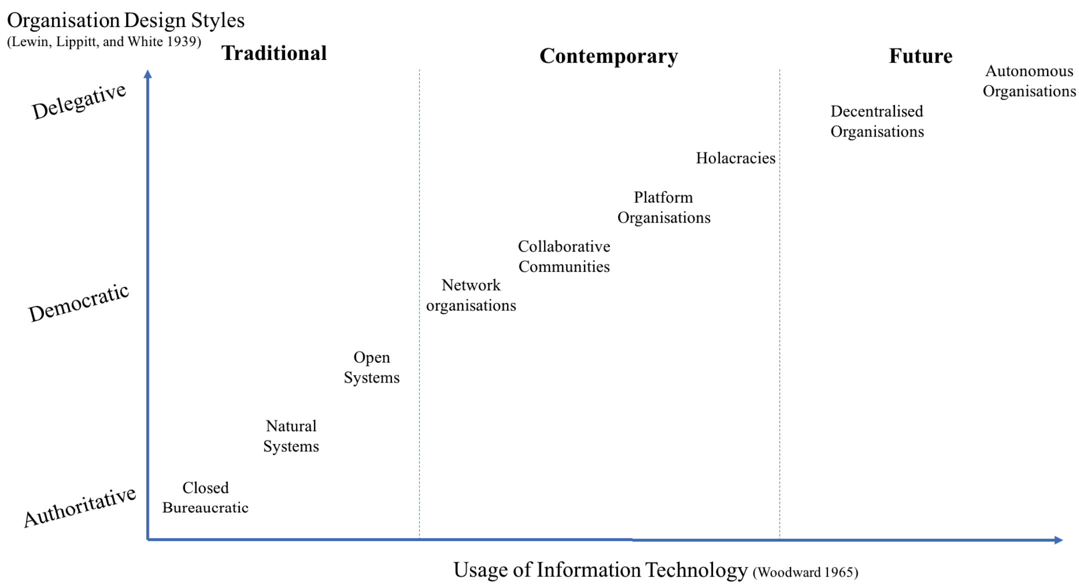

Figure 11: Conceptual Framework

Of course, the advances made within the blockchain ecosystem do not automatically imply the complete abandonment of existing organisational models. On the contrary, we will see an overlap between new and old technologies, but overtime distributed ledger technologies will bring organisations closer to a DAO. In addition, we do not argue that decision-making within *decentralised* and *autonomous* organisations is superior to human decision-making as that requires further research.

A Research Agenda

New technologies can lead to conflict, changing or challenging existing power distributions and/or decision-making capabilities (Orlikowski and Robey 1991). As a nascent technology, the number of organisations that have successfully developed and implemented decentralised applications is low. Consequently, there is limited research available on the impact of blockchain on strategic management, organisation design (such as decision-making or power distributions) and corporate governance. Although it is likely that blockchain technologies will fundamentally change how organisations are managed and operated in the future, more research needs to be undertaken on the implications for strategic management, organisation design and governance. Given these possibilities, we feel that future research could address a range of questions. For example:

- How do the two new forms of organisation design (i.e., decentralised and autonomous) affect organisation design theory?
- Is it necessary to review existing theories?

Smart contracts will automate decision-making, but how will smart contracts change decision-making capabilities within decentralised and distributed organisations? Other questions in this vein include:

- How will automated decision-making change internal, centralised, organisational structures and organisation design?

- Will smart contracts change the behavioural theory of the firm (Cyert and March 1963)?
- Does the incomplete contracting paradigm, as developed by Grossman and Hart (1986), Hart and Moore (1990), and Hart (1995), apply to DAOs?

Once there is a clear understanding of the impact of distributed ledger technologies on decision-making, researchers can focus on the broader effect of a DAO on society, individuals and shareholders. Questions might include:

- How does a DAO fit in existing literature on organisation design given that it does not employ any management or employees?

This is likely to be a longitudinal study to fully understand how a DAO evolves from idea to implementation. Following on from this, researchers could ask:

- How can corporate and data governance be engineered into code (smart contracts) and recorded on a blockchain from an organisational perspective (O'Dwyer 2015)?
- How could a DAO deal with contradictory regulatory requirements when operating distributed across borders?
- What steps could organisations take to transform a traditional (network) organisation into a DAO?

Finally, we feel that it is important to attempt to determine whether decision-making enabled by cryptography, smart contracting or governance embedded in code is superior to existing human decision-making. Researchers can potentially answer these questions by focusing on existing organisations that incorporate blockchain and smart contracts within their organisation (e.g., the financial services organisations discussed in this paper) or by researching new blockchain startups that are developing DAOs.

In general, it seems that Blockchain and smart contracts are likely to have a significant effect and that DAOs are likely to change the playing field. Therefore, most of the existing theories on organisation design and governance will have to be reviewed to make way for an organisation design that has neither managers nor employees but is run completely by immutable computer code.

Implications for Practitioners

As we have seen in this conceptual paper, Blockchain is a disruptive technology that is likely to drastically change organisation design and decision-making. The fact that blockchains are distributed and decentralised (i.e., no single party can control the ledger and cryptography ensures a trustless system, removing the need for intermediaries) is a true paradigm shift. Many new blockchain startups are being developed that raise millions through initial coin offerings in a matter of hours, days or weeks, disrupting incumbent firms in unexpected ways. Especially for intermediaries such as banks, real estate agents or notaries, blockchain and smart contracts can pose a significant threat. Therefore, it is incumbent on managers to be aware of the possibilities of Blockchain and to investigate both how Blockchain affects their organisation and how smart contracts can be applied within the organisation to start automating decision-making capabilities.

Conclusion

New forms of organisation design, both decentralised and autonomous, will likely appear due to the emergence of Blockchain and smart contracts. By ensuring a single version of the truth of ownership, Blockchain removes the need for trusted intermediaries and enables irrefutable transactions and decisions to be executed automatically and autonomously across time and space. Organisations that apply Blockchain are increasingly becoming part of a distributed network organisation as part of the 'Internet of Value'. When organisations start using smart contracts that are deployed on a blockchain, they move towards becoming a DAO in which actors of all kinds self-organise to create value. Governance, whether implemented within the code or ensured through the right processes within the organisation, is vital because of the irrevocable code that is deployed and the data that are stored on a blockchain. In addition, DAOs must ensure that they comply with regulatory requirements that may or may not be contradictory.

Blockchain offers tremendous opportunity for organisations to create value, develop new products and services, automate strategic decision-making and reduce intermediaries, resulting in new forms of organisation design. However, there are considerable governance and technological challenges to be overcome; therefore, significantly more research is required.

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[i] This paper follows industry practices in the writing of Bitcoin vs bitcoin and Blockchain vs blockchain. When written as Bitcoin, it relates to the technology; when written as bitcoin, it relates to the cryptocurrency. The same goes for Blockchain, which refers to the technology/trend as a whole and blockchain, which means one or more blockchain(s) (i.e., a distributed ledger database).

[ii] As Lewin, Lippitt, and White (1939) observed, there are three leadership styles when it comes to making decisions: autocratic, or authoritative, in which leaders make decisions themselves; democratic, in which leaders involve others in the decision-making process; and laissez-faire, or delegative, in which decisions are made by a leader's followers.

[iii] Cryptography is a key component of any distributed ledger technology. It consists of two important fields: the digital signature and the hash algorithm. Cryptographic primitives (algorithms that are used

to develop cryptographic protocols) are an important component of decentralised organisations, as it is cryptography that enables trustless transactions among different actors.

[iv] It should be noted that the technological developments around Blockchain are so rapid that, by the time you read this, this could be outdated.

[v] The PoW algorithm is used in public, or permissionless blockchains, in which actors do not have to know or trust each other. As such, it is used in the bitcoin blockchain, which is a public blockchain. This consensus algorithm requires participating actors to solve a difficult computational problem to validate the blocks. The validation is performed using cryptography, which means the actor has to find the solution of an inequality, which requires considerable computing power (and energy). When a solution is presented, it is immediately clear that it is correct. This can be compared to a crossword puzzle, which can be difficult to solve, but once completed you immediately know that it is correct. The moment an actor has solved the equation, the solution is presented to the whole network and the actor receives bitcoins as a reward (in the case of the bitcoin blockchain).

[vi] Within PoS, as within PoW, validators are selected randomly; however, whereas validators within PoW have a larger chance of being selected if they have more computing power, within PoS the amount of money (i.e., the number of tokens or the amount of cryptocurrency) determines the likelihood of being selected (Pîrjan et al. 2015). Once a block is produced, a transaction fee is paid to that validator and signers commit the block to the blockchain. These signers can be all nodes in the network or a randomly selected group of nodes that determine it for the complete network. To incentivise nodes to hold a larger stake, the puzzles are made easier the more stake one has. As a result, PoS requires far fewer CPU computations and, therefore, is more energy efficient (Christidis and Devetsikiotis 2016). The assumption underlying PoS is simple; if an actor has a higher stake in the system, it has a higher incentive to ensure the network is secure and correct because of the pain felt when the price and reputation of the cryptocurrency is damaged due to attacks. It is expected that the Ethereum network will implement a PoS consensus mechanism in 2018.

[vii] The reader may argue that cryptocurrency exchanges are also centralised intermediaries that take a commission for verifying cryptocurrency transactions. Although that is correct, we will ignore this in our paper since we do not focus on the blockchain application of cryptocurrencies, but we focus on the fundamental technology of blockchain. In addition, although exchanges are required to exchange one cryptocurrency for another, they are not required for performing transactions with a single cryptocurrency. Finally, increasingly decentralised cryptocurrencies exchanges are being developed that aim to replace centralised exchanges as these are prone to attacks by hackers. However, it should be noted that blockchain technology is very secure. The bitcoin blockchain has been around for 10 years and has not yet been hacked. The problem lies with the centralised exchanges.

[viii] The bitcoin blockchain grows steadily. For the size of the blockchain in November 2018, see https://blockchain.info/nl/charts/blocks-size

[ix] See https://twitter.com/VitalikButerin/status/695989627249782784

[x] Mining Pools are groups of cooperating miners who agree to share block rewards in proportion to their contributed mining hash power.

[xi] It is likely that the concepts of cryptography, consensus mechanisms and smart contracts will affect more organisational theories but discussing how Blockchain will affect each and any of these theories would be beyond the purpose of this paper. Therefore, we have opted to only briefly discuss these theories.

4.3 Paper 3: How to build Responsible AI: A conversation with Tay and lessons for governance practices

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Keywords: Artificial Intelligence, governance, data

Abstract

Artificial intelligence (AI) is intelligence displayed by a computer that perceives its surroundings and acts autonomously towards achieving its objectives. The development and adoption of AI has progressed so much in recent years, that both scientists and business executives are now realising the importance of creating safe and, specifically, Responsible AI. Some have made mistakes when developing and deploying AI that caused harm to users and other actors affected by or involved with AI. The development of conversational AI, also known as chatbots, serves as a popular example. Here, we discuss the case of Microsoft's chatbot *Tay*, which posted inflammatory, offensive and racist tweets on Twitter in 2016, and review 20 other cases of organisations that developed chatbots in recent years. The *Tay* case confirmed that developing AI is not without risks. With the objective to recognise, theorise and refine governance mechanisms that ensure responsible (conversational) AI, we set out to talk to organisations and learn about current professional practices to guarantee AI is acting responsibly. We discuss our observations using an agency theoretic perspective. Our theoretical framework contributes to organisational governance literature and its application to an emerging, technology driven phenomenon. Our research will help practitioners understand what governance practices could be implemented to ensure Responsible AI and enhance user's trust in AI systems.

Introduction

On March 23, 2016, Microsoft Corporation launched an artificial intelligence (AI) chatbot on Twitter, called *Tay*. *Tay*'s objective was to have conversations with Twitter users, learn from these interactions and improve its conversations. However, after only 16 hours and 96,000 tweets, Microsoft took *Tay* offline as it had tweeted inappropriate, inflammatory, offensive and racist messages. This incident resulted not only in a public relations disaster for Microsoft (Hern 2016, Vincent 2016, Murgia 2016) but a global uproar and new impetus for the public debate on the morals of AI. The *Tay* case showed how AI may act differently in a real setting than during testing in a controlled environment (Garcia 2016). In addition, it showed that chatbots are generative digital artefacts that continuously change and evolve as it is difficult to contain them in a real environment (Yoo 2012). It also showed that biased data can negatively affect business outcomes—in this case, sizeable damage to the Microsoft brand (Hern 2016). There are further instances of biased data and poorly designed algorithms resulting in, for example, good teachers being fired after school performances were analysed by AI (O'Neil 2016), or consistently labelling black criminals a higher risk than white criminals (Spielkamp 2017). While AI is rapidly impacting all aspects of society and is starting to make up for its promise (Yudkowsky 2008), it is not without risks (Luca, Kleinberg, and Mullainathan 2016), especially as it evolves into so-called artificial general intelligence (AGI), which is AI that is as intelligent as humans and able to solve a wide array of problems, not just specific narrow tasks (Bostrom 2014). Here we follow the common definition of AI as intelligence exhibited by computers that perceive their environment and take action to maximise their goal (Bostrom 2014, Russell and Norvig 1995); yet, we note that, so far, it is not evident that AI behaves as humans have designed it (Bostrom 2014). There is a need for further study on what governance would look like when organisations are implementing AI. We need a better understanding of what can be done to ensure AI behaves as planned.

In recent years, a continuous stream of AI breakthroughs have been possible due to increased 'computational capabilities, algorithm design and communication technology' (Alfonseca et al. 2016, 1), resulting in the emergence of algorithmic businesses that rely on complex algorithms and AI to automate business processes and improve decision-making (Prentice 2016), such as the Hong Kong venture capital firm Deep Knowledge Ventures, who appointed an algorithm to its board of directors to improve decision-making (Hanson 2017). Using AI is as much a natural evolution as the transition to digital business models that many organisations have been through in recent years. New value can be created, thanks to AI (Prentice 2016). AI algorithms are likely taking over jobs, resulting in significant loss of human work (Ford 2015, Hawksworth 2018, Furman 2016) and will contribute to efficiency gains for many organisations. Take call centres, where conversational AI, also known as chatbots, is taking over much of the work previously performed by call centre agents (Accenture 2017). The positive impact of AI on the global economy is estimated to reach US$15.7 trillion by 2030 (Rao and Verweij 2017). However, the challenges and impact of AI have also become more visible. The *Tay* case serves as a warning, and there are growing concerns that in the decades to come AI may in fact be harmful to humanity (Müller and Bostrom 2016b). Discussion of AI as a potentially catastrophic technology has reached academia. The idea of AI as 'existential risk' (Alfonseca et al. 2016, 1) has enticed several scholars to examine the subject and conclude by emphasising how important it is to develop safe AI (Russell, Dewey, and Tegmark 2015, Anderson 2015b). So far, there have been numerous occasions of AI gone rogue

(O'Neil 2016) and inflicting tremendous damage (Luca, Kleinberg, and Mullainathan 2016). A recent example is the death caused by the self-driving Uber taxi (Turchin and Denkenberger 2018). Even if chances are low, these risks should be taken serious because of what is at stake, and the ease with which AI can be scaled and fooled (Barrett and Baum 2016).

Moor (2005) argues that ethical problems will increase as technologies improve and develop into mutually enabling technologies, as is the case with AI that uses reinforcement learning to improve itself, unsupervised, and in ways humans may not understand (Bostrom 2014). In such cases, governance is important to ensure high-quality, non-biased, data (O'Neil 2016) is used and algorithms are developed in line with existing, as well as future, norms, values and ethics (Anderson, Anderson, and Armen 2004, Moor 2005, Reynolds 2011, Anderson and Anderson 2011). As the *Tay* chatbot example shows, AI, particularly machine learning, relies on input data that is used to train the algorithm and develop the rules that govern it. As a consequence, AI is not immune to the '*garbage in, garbage out'* imperative (Musib et al. 2017) and organisations should prevent the use of biased data when dealing with AI (O'Neil 2016). Other scholars argue the need for information technology (IT) ethics, which is the ethical behaviour of information systems and their employees (Banerjee, Cronan, and Jones 1998, Tavani 2003, Reynolds 2011). With the rise of intelligent machines, this is gradually moving towards machine ethics, focused on how algorithms and machines can behave ethically now and in the future (Satell 2016, Anderson and Anderson 2011). In past decades, IT ethics and governance have played an increasingly important role and while many researchers have focused on these topics (Reynolds 2011, Tavani 2003, Sarsfield 2009, Bruwer and Rudman 2015), we need to continue to do so when considering AI.

While data governance practices can help prevent biased data (Alhassan, Sammon, and Daly 2016, Malik 2013, Egli 2016, Asadi Someh et al. 2016), it does not solve the issue that AI does not always behave as intended (Pistono and Yampolskiy 2016, Bostrom 2014, Yudkowsky 2011, Armstrong, Sandberg, and Bostrom 2012, Soares 2015). It is a common problem in the development of AI, as it is difficult to capture all complexities of human endeavours and intentions when developing the goal or objective of AI (Soares 2015). The problems with *Tay* are a clear example of the consequences when an artificial agent behaves differently than intended by the developer. This problem is commonly known as the principal–agent problem and is especially known within organisations where the agent, often the board of directors, behaves differently than intended by the principal, often the owners of the organisation, because both actors have different objectives (Ross 1973).

To reiterate, various scholars and organisations see the need for (data) governance processes to ensure high-quality data and the need for IT ethics when dealing with data and AI. While existing corporate governance practices help solve the principal–agent problem when the agent is human (Hillman and Dalziel 2003), little research is available on the corporate governance practices required when dealing with artificial agents to ensure AI behaves as planned, has no flaws, and does not harm the human actors involved; that is, ensuring it behaves as planned by the principal. These issues are especially pressing as AI evolves into AGI or even super artificial intelligence (SAI), which amplifies the effect and risks for humanity.

Here, we seek to expand existing governance perspectives and offer further governance practices to enable organisations to develop governance frameworks for AI that limit the likelihood of AI harming any human actor involved. In other words, we seek to solve the AI principal–agent problem when dealing with artificially intelligent agents to ensure safe and Responsible AI that behaves as intended and does not harm those actors involved, which we refer to as Responsible AI. Thus, our research question is: *What are the governance practices that allow an organisation to ensure Responsible AI?* We propose to answer this question via a qualitative study of organisations that have developed and/or implemented AI in the form of a chatbot.

First, we discuss the theoretical background related to various forms of AI and the existing mechanisms in the literature suggesting how to solve the principal–agent problem when dealing with AI. Then we consider the role of existing governance practices within the management of organisations in solving the principal–agent problem when dealing with human agents. Based on the existing AI literature, we then propose a framework that will be used in developing the qualitative research, which is discussed in the methodology section. Finally, we review the results and offer some further guidance for organisations on how to best address the principal–agent problem inherent in dealing with artificial agents. We conclude with the limitations of this study and a proposed agenda for further research into this emerging and important phenomenon.

Theoretical Background

Artificial Intelligence

There are three forms of AI: narrow AI, AGI and SAI (Bostrom 2014). Narrow AI refers to AI that can outperform humans on specific tasks in relatively narrow domains (Baum, Goertzel, and Goertzel 2011); for example, a trading algorithm or Google Translate on your smart phone. AGI refers to AI systems having autonomous self-control and self-understanding and the ability to learn new things to solve a wide variety of problems in different contexts (Goertzel and Pennachin 2007); for example, imagine an application capable of driving your car, doing your accountancy or making you a coffee. The final phase of intelligence is SAI, which is intelligence far exceeding that of any person, however clever (Bostrom 2014, Good 1966). SAI would be able to manipulate and control humans and achieve domination.

The development of AI results in an increasing convergence of the human and the computer (Roco and Bainbridge 2003, Hayles 2005, Gershman, Horvitz, and Tenenbaum 2015), resulting in social, technological, political and ethical implications where AI and humans are becoming increasingly interwoven in mutually dependent networks (Fleischmann 2009). This is especially visible in areas where chatbots are implemented, as humans are directly interacting with AI (Zamora 2017). Within such human–machine networks, actors may interact differently and, therefore, an analysis of both artificial and non-artificial agents in the same context, avoiding the need to think in human/non-human barriers (Latour 2005b) is required—especially when dealing with SAI agents.

Dangers of SAI

SAI is likely to be developed in the (near) future (Bostrom 2014, Shulman and Bostrom 2012, Moravec 1976). How it will look is still unknown, but it will be fundamentally different to human intelligence (Ayoub and Payne 2016). Intelligence is ‘the complex expression of a complex set of principles’ (Yudkowsky 2007, 389), which consists of multiple interdependent subsystems linked to each other. Intelligence exists because of evolution and enables humans to model, predict and manipulate reality. It enables us to reason backwards and forwards from a mental image, and reason on desired future outcomes (Yudkowsky 2007). Evolution created intelligence, but evolution does not possess this foresight. In fact, this evolutionary process is an unintelligent process and has resulted in flaws in human intelligence (Yudkowsky 2008). Due to various constrains such as food availability and trade-offs with other organs or biological materials, our brains might not have evolved in the most optimised way (Armstrong, Sandberg, and Bostrom 2012). Since AI is developed by (artificial) intelligent actors with foresight capabilities that evolution misses (Yudkowsky 2007), and uses materials and processes better suited for intelligence, SAI could result in new forms of intelligence unfamiliar to humankind today (Armstrong, Sandberg, and Bostrom 2012, Bostrom 2014). Hence, a different approach to ensuring safe AI is required.

SAI is likely to occur as part of an 'intelligent explosion' (Good 1966), when AGI, thanks to rapid cycles of self-improvement and reinforcement learning, reaches a stage of super intelligence that far exceeds the combined intelligence of humankind (Bostrom 2014). This transition to SAI could last several seconds, multiple months, or years (Bostrom 2014). However, humans tend to anthropomorphise AI and see AGI on the scale of the village idiot–Einstein. This seriously underestimates the potential impact of AI, as the aforementioned scale is a mere dot on the complete scale of all possible forms of intelligence (Yudkowsky 2008). Therefore, it can come at a price if governance and ethics are not incorporated in the development of AI (Anderson, Anderson, and Armen 2004). The more sophisticated AI becomes, the less obvious its behaviour becomes to the user (Van Lent, Fisher, and Mancuso 2004). No one should make assumptions of SAI's behaviour, except that it will have full access to its source code and can overrule any control mechanisms (Alfonseca et al. 2016, Bostrom 2014). Therefore, it is important to only build AI that we fully understand (Yudkowsky 2008, Bostrom 2014), to prepare organisations for situations that they cannot imagine today—which requires flexibility in design and processes (Bostrom and Yudkowsky

2014)—and to have a thorough theoretical understanding of how and why an artificial agent will make decisions in future, unexpected scenarios (Soares and Fallenstein 2015). The latter increases the problem, as building AI that behaves as we want it to behave—so-called Responsible AI—requires taking into account future design requirements to prevent future expensive fixes such as the Y2K computer bug (Yudkowsky 2008, Huang, Newell, and Pan 2001). Super intelligent machines may be the last invention humankind need ever make (Good 1966); however, if we do it incorrectly it may result in the end of humankind (Bostrom 2014, Russell and Norvig 1995, Bostrom 2002).

Need for Responsible AI

Turing (1950, 460) hoped that machines would eventually 'compete with men in all purely intellectual fields'. Such super intelligent machines would transform societies in unimaginable ways. As Good (1966, P34) stated, these 'machines will be feared and respected, and perhaps even loved'. Since these early statements, AI research has been overpromising and under delivering for decades, resulting in several AI-winters (Yudkowsky 2008) and diverting fear of existential risks by AI to the fantasy world (Alfonseca et al. 2016). However, due to new successful applications of AI in a variety of domains, driven by tech giants such as Google, Facebook, Tencent, Baidu, Apple and Microsoft, there has been increased attention on AI as a catastrophic risk (Barrett and Baum 2016). This has resulted in open source initiatives such as OpenAI, a non-profit AI research company with the stated objective to 'advance digital intelligence in the way that is most likely to benefit humanity as a whole'.

Failures in achieving Responsible AI can be divided in two, non-mutually exclusive categories: philosophical failure and technical failure (Yudkowsky 2008).

Researchers can build the wrong thing, so that even if SAI is achieved, it will not be beneficial to humankind; or researchers can attempt to do the right thing, but fail because of a lack of technical expertise, which would prevent us from achieving SAI in the first place. The border between these two failures is thin, because 'in theory you ought first to say what you *want*, then figure out *how* to get it. In practice, it often takes a deep technical understanding to figure out what you want' (Yudkowsky 2008, 13). Not everyone believes in the existential risks of AI, simply because they say SAI will not cause any problems or because existential risks do exist, AI itself will solve these risks, meaning that in both instances nothing happens (Anderson 2015b). Nevertheless, SAI is likely to be extremely powerful (Good 1966) and dangerous (Yudkowsky 2008, Bostrom and Yudkowsky 2014) if not controlled properly (Armstrong, Sandberg, and Bostrom 2012), simply because SAI could reshape the world according to its preferences, which may not be human-friendly and capable of resisting any human control (Armstrong, Bostrom, and Shulman 2016). As such, SAI offers different risks than any other known existential risk humans faced before, such as nuclear war, and requires a fundamentally different approach.

Importance of Explainable AI (XAI)

AI learns from its environment and improves over time due to deep learning and machine learning. Although such learning allows AI to rework its internal workings, AI is not yet sentient, cognisant or self-aware; that is, it cannot interpret meaning from data (Ayoub and Payne 2016). AI is not limited by information overload, complex and dynamic situations, lack of complete understanding of the environment (due to unknown unknowns), or overconfidence in its own knowledge or influence, since it can take into account all available data, information and knowledge and is not influenced by emotions (Ayoub and Payne 2016). However, as Ayoub and Payne (2016) argue, AI might recognise a cat, but it does not know what a cat is; that is, to the AI, a cat is a collection of pixel intensities, not a carnivorous mammal often kept as an indoor pet. In addition, AI has fundamentally different motivations than humans (Müller and Bostrom 2016a, Neisser 1963, Kuhl and Kazen-Saad 1988). Humans are driven by money, sex and status, while existing AI is logical and probabilistically driven (Gill 2016, Bostrom 2014). That does not mean AI decisions are error free. On the contrary, as we have seen with *Tay*. AI 'preserves the biases inherent in the dataset and its underlying code' (Ayoub and Payne 2016, 799), resulting in biased outputs that could inflict significant damage (O'Neil 2016). Hence, when AI can collect unbiased data, for example through unbiased sensors, unbiased automated decision-making becomes possible. However, unbiased data alone is not enough, as algorithms are also affected by the cognitive bias of human designers. Bias can also appear in the selection and tweaking of an algorithm by the data scientist, even when the machine learning algorithm did not require any data. Consequently, achieving unbiased algorithms is highly challenging, especially when the rationale of the algorithm is not clear. Often, researchers can only see the actions of AI and infer the strategy from this, but cannot see the reasoning behind it (Gill 2016, Bostrom 2014, Ayoub and Payne 2016), which is why researchers are working on developing explainable AI (XAI) (Soares 2015, Abadi and Andersen 2016, Van Lent, Fisher, and Mancuso 2004, Core et al. 2006, Taylor, Knudsen, and Holt 2006) to help us understand why a certain decision was made (Luca, Kleinberg, and Mullainathan 2016, Lomas et al. 2012).

Algorithms are black boxes (Pasquale 2015) and XAI relates to explanatory capabilities within an algorithm to help understand why certain decisions were made

(Luca, Kleinberg, and Mullainathan 2016). The more sophisticated AI becomes, the less obvious its behaviour becomes to the user of AI (Van Lent, Fisher, and Mancuso 2004). With machines getting more responsibilities, they should be held accountable for their actions (Anderson, Anderson, and Armen 2004, Sotala 2015). XAI should present the user with an easily understandable chain of reasoning for its decision (Van Lent, Fisher, and Mancuso 2004, Core et al. 2006). When AI is capable of asking itself the right questions at the right moment to explain a certain action or situation, basically debugging its own code (Lomas et al. 2012), it can create trust and improve the overall system (Taylor, Knudsen, and Holt 2006), especially if it is able to explain its actions in 'human-understandable concepts and terms' (Lomas et al. 2012, 1). XAI can be useful for developers to create better, more trustworthy algorithms, which in the end could lead to Responsible AI.

Incorporating AI Ethics

However, XAI does not mean ethical AI, which is completely different. Achieving AI that can behave ethically is an enormous challenge (Hurtado 2016, Bostrom and Yudkowsky 2014, Anderson and Anderson 2011), since ethics can be variable, contextual, complex and changeable. The ethics we valued 300 years ago, such as slavery, are not ethical in today's world and what we deem ethical today might be illegal tomorrow. As such, we do not want ethics in AI to be fixed, as this could limit its potential and affect humankind (Bostrom and Yudkowsky 2014). AI ethics is a difficult field because future behaviour of advanced forms of a self-improving AI are difficult to understand if the AI changes its inner workings without providing insights on it; hence, the need for XAI. Therefore, ethics should be part of AI design to ensure ethics is part of the code; that is, bringing ethics to the code (Bostrom and

Yudkowsky 2014). However, some scholars argue that ethical choices can only be made by beings that have emotions, since ethical choices are generally motivated by these (de Spinoza 2016/1677, Hume 2003, Brooks 2009). De Spinoza (2016/1677) defines moral agency as 'emotionally motivated rational action to preserve one's own physical and mental existence within a community of other rational actors', but how would that affect artificial agents and how would AI ethics change if one sees AI as moral things that are sentient and sapient? As Bostrom and Yudkowsky (2014, 13) argue, 'when thinking about applied ethics for contexts that are different from our familiar human condition, we must be careful not to mistake mid-level ethical principles for foundational normative truths'. In addition, the problem we face when developing AI ethics, or machine ethics, is that it relates to *good* and *bad* decisions. Yet, it is unclear what *good* or *bad* means, as it means something different for everyone across time and space. Furthermore, machine ethics are likely to be superior to human ethics. First, humans tend to estimate, while machines can precisely calculate the outcome of a decision (Anderson, Anderson, and Armen 2004). Second, humans do not necessarily consider all options and may favour partiality, while machines can consider all options and be strictly impartial. Third, machines are unemotional, while with humans, emotions can limit decision-making capabilities. Although it is likely AI ethics will be superior to human ethics, it is still far away and the technical challenges to instil ethics within algorithms are numerous (Bostrom 2014). This is why Moor (2005) argues for better and increased attention to ethics for emerging technologies such as AI, because as their social impact increases, ethical problems increase as well. However, behaviour of AI is not only influenced by the mathematical models that make up the algorithm, but also directly influenced by the data the algorithm processes, since poorly prepared or biased data results in incorrect outcomes: ‘*garbage in is garbage out’* (O'Neil 2016). While incorporating ethical behaviour in mathematical models is a daunting task, reducing bias in data can be achieved more easily using data governance (Egli 2016, Asadi Someh et al. 2016).

High-quality, unbiased data, combined with the right processes to ensure ethical behaviour within a digital environment could significantly contribute to AI that can behave ethically (O'Neil 2016). Of course, from a technical standpoint ethics is more than just usage of high-quality, unbiased data and having the right IT processes in place. It includes instilling AI with the right ethical values that are flexible enough to change over time. Bostrom (2014) argues that the theoretical concept of coherent extrapolated volition (CEV) is our best option to instil the values of humankind in AI. CEV takes into considerations the morals and values we have not yet developed and removes those that might be wrong, or as Yudkowsky (2004, 6) states in poetic terms, CEV is how we would build AI if ‘we knew more, thought faster, were more the people we wished we were, had grown up farther together; where the extrapolation converges rather than diverges, where our wishes cohere rather than interfere; extrapolated as we wish that extrapolated, interpreted as we with that interpreted’. As may be clear by CEV, AI ethics is a highly challenging field that requires special attention if we wish to build Responsible AI, and those actors involved in developing AGI and SAI could play a key role in achieving AI ethics. XAI and AI ethics are one approach to Responsible AI. The other approach to achieving Responsible AI is to prevent bad AI from happening in the first place. Hence, the need for control methods when developing AI.

Control Methods

To understand the impact of (super) AI, human–machine networks (HMNs), which are intensely connected (Tsvetkova et al. 2017), could be seen as nodes having multiple dimensions with each other, whereby actors are more like flows that interact with each other and thus, change (Latour 2005b). As Latour (1996a, 7) argues, an actor is semiotic. It is 'something that acts or to which activity is granted by others', which is the case with AI. It is important to understand which mode of action actors are engaged in, and ensure actors account for their actions. This determines how groups function (Latour 2005b), which is why XAI is so important. Without AI being accountable for its actions and offering feedback (reflexivity), a network will malfunction (Latour 2005b). When dealing with AI, it is important to understand how a group operates, who interacts, who or what takes action, how to re-apply social connections when actors change, and how existing actors can influence SAI (Feldman et al. 2016, Sele and Grand 2016). To do so, we should 'localise the global' (Latour 2005b, 173); that is, map the connections and define interactions among human–machine actors.

Networks combining social participation and machine-based computation, where humans and machines interact with each other to produce synergistic effects, are constantly evolving. Such networks are analysed using emerging theory on social machines (Shadbolt et al. 2013, Smart, Simperl, and Shadbolt 2014, Buregio, Meira, and Rosa 2013). Within HMNs, social interactions become more important, interactions less demanding and machine–human interactions more prominent (Tsvetkova et al. 2017), as can be seen in the appearance of chatbots in call centres. Agents within such HMNs create outputs that neither a pure social network nor a pure machine network are able to create independently. AI enables new forms of interaction between humans, resulting in interactions with different levels of intensity and involvement (Tsvetkova et al. 2017). Networks involving some sort of technology can create complicated strategies involving unexpected technical and social implications (Callon 1990). Already, this behaviour is showing in AI-only networks, where algorithms start competing against each other (Leibo et al. 2017), develop new encryption methods (Abadi and Andersen 2016), or create their own secret language unsolicited (Lewis et al. 2017). The behaviour of actors changes the state of the network, which is itself the product of previous actions (Callon 1990). As a result, a self-reinforcing feedback loop can result in unexpected behaviour (Bostrom 2014). The challenge is to understand how we can prevent AI agents behaving in ways that do not comply with the intention of the developers.

Callon (1984) calls this 'interessement'; that is, actions some actors take to impose and stabilise other actors. Different devices can be used to implement such actions, which, in the case of AI, Bostrom (2014) calls control methods. Such control methods should be implemented to solve the principal–agent problem (Bostrom 2014), where the agent acts differently than the principal intended. There are a wide variety of technical methods used to address the problem, such as ensuring interpretability (Abel, MacGlashan, and Littman 2016), capability control methods or motivation selection methods (Bostrom 2014). There are also several non-technical safety measures actors can take to prevent bad AI, including oversight, governance and AI audits (Bostrom 2014, O'Neil 2016, Mayer-Schönberger and Cukier 2013). However, it is unclear whether such safety methods would be sufficient to ensure responsible SAI (Bostrom 2014). Therefore, we will examine existing (corporate) governance theory to understand what mechanisms can be applied to ensure Responsible AI.

Agency Theory

Overall, AI clearly has the potential to completely change organisations and societies for better or worse. However, we do not yet know how organisations and societies can contribute to ensure Responsible AI and how organisations can ensure XAI, machine ethics or implement control methods. Research on corporate governance mechanisms for AI is limited; therefore, we draw from existing corporate governance theory related to the principal–agent problem to understand what organisations can do when involved with AI. To do so, we consider existing agency theory literature, which aims to understand how the principal can ensure the agent acts in the best interest of the principal.

Agency theory defines a distinction between the owners of an organisation and the management of the organisation (Johnson, Daily, and Ellstrand 1996), whereby the management (the agent) has different objectives and goals than the owner (the principal). As a result, the owner receives a lesser return on investment, since they do not manage the company themselves (Eisenhardt 1989a). This has been defined as the principal–agent problem and is a dilemma where the agent acts in their own best interest, which may be contrary to those of the principal. It is one of the oldest and most common modes of interaction (Ross 1973). From an agency theory perspective, as Hillman and Dalziel (2003) argue, a board tends to exercise strict control, supervision and monitoring to ensure the agent performs in the best interest of the principal. Hence, agency theory in general, and specifically the principal–agent problem, are relevant to AI, as often an AI Agent acts differently than the developer (the principal) intended (Bostrom 2014).

Traditionally, governance literature has focused on ensuring different stakeholders within an organisation are aligned (Aguilera and Jackson 2003, John and

Senbet 1998, Kock, Santaló, and Diestre 2012, Hill and Jones 1992). It focuses on the relationship and interactions between different groups; for example, the directors of an organisation, the board of an organisation and the owners of an organisation, who all may have different objectives and perspectives. Corporate governance can then be used to better align these objectives and perspectives, which is beneficial for an organisation. In agency theory, this tends to be done by the principal exercising control, monitoring the performance of the agent and supervising the agent to protect the principal's interests (Hillman and Dalziel 2003):

Control is exercised through strategic and financial control methods (Baysinger and Hoskisson 1990). Financial control relates to ex ante mechanisms (budgets) and ex post mechanisms (whether key performance indicators [KPIs] have been reached) (Baysinger and Hoskisson 1990, Hoskisson, Hitt, and Hill 1993, Ravenscraft 1996). Strategic control relates to the decision-making capabilities of directors and the success of their decisions (Baysinger and Hoskisson 1990, Gupta 1987).

Monitoring is exercised through a board (the principal) monitoring the actions of the management (the agent) (Eisenhardt 1989a, Hillman and Dalziel 2003, Jensen and Meckling 1976, Mizruchi 1983), including monitoring the implementation of strategy (Rindova 1999), planning the succession of the CEO (Pitcher, Chreim, and Kisfalvi 2000) and evaluating and consequently rewarding C-level executives (Boyd 1994, Conyon and Peck 1998). All monitoring activities have the objective to protect the interests of the principal (Hillman and Dalziel 2003).

Supervision can be exercised through coaching and mentoring of the agent by the principal. When required, an organisation's board can move from a monitoring role to a more active role of coaching and providing feedback to try to steer the agent in the right direction to protect its interests (Strebel 2004, Christen, Iyer, and Soberman 2006, Hilb 2008).

These existing corporate governance mechanisms of controlling, monitoring and supervising to solve the principal–agent problem work well when both agent and principal are human. However, strategic and financial control methods, succession planning or monetary rewards, and coaching or mentoring no longer work when the agent is artificial, as AI is not driven by human motivations, only logic (Ayoub and Payne 2016, Soares and Fallenstein 2014, Fallenstein and Soares 2015). Therefore, when dealing with an artificial agent, existing mechanisms need to be adjusted to fit the characteristics of the artificial agent. Solving the principal–agent problem when dealing with artificial agents could help organisations develop Responsible AI, where organisations exercise strict control, supervision and monitoring on the performance of AI. Therefore, the aim of our research is to understand what control, monitoring and supervising mechanisms organisations can implement when dealing with AI to ensure the artificial agent behaves in the best interest of the principal.

Theoretical Framework

Following aforementioned literature on AI and Bostrom's (2014) views to solve the principal–agent problem, combined with existing corporate governance mechanisms to solve the principal–agent problem in organisations, we argue there are three approaches that could contribute to Responsible AI: XAI, to have AI explain itself; AI ethics, to ensure AI behaves ethically now and in the future; and control methods to contain AI and prevent it from doing any harm to those actors involved. We link this to the controlling, monitoring and supervising mechanisms of agency theory to understand how they could be adjusted when dealing with AI. Therefore, in this study we investigate how the principal–agent problem can be solved when dealing with artificial agents. This leads to the theoretical framework underpinning our research, as shown in Figure 12. The theoretical framework guided us in developing interview questions for our qualitative research.

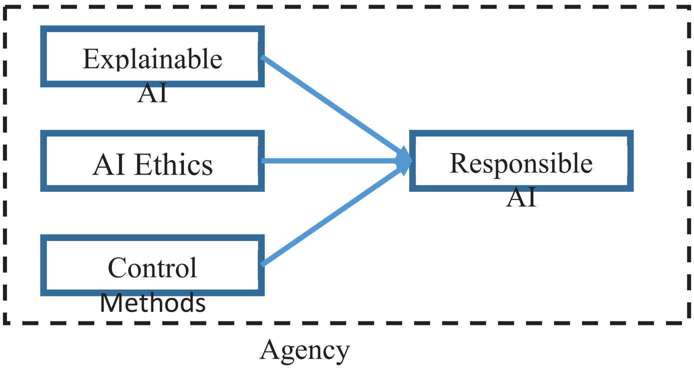

Figure 12: Theoretical framework to guide the qualitative research

In the second part of this paper, we use agency theory in general, and the controlling, monitoring and supervising mechanisms specifically, to understand what organisations can do to ensure Responsible AI. We will do so using data collected from 20 organisations around the globe who are involved with developing conversational AI (chatbots). We define chatbots as an artificial agent that uses AI to hold conversations with human agents. The problems with *Tay* show that even in seemingly harmless environments such as online conversations, AI can be damaging if developed irresponsibly. Therefore, we set out to understand what organisations are doing to develop responsible conversational AI, which can inform us how to ensure Responsible AI.

Methodology

We adopted a qualitative research approach to understand how different organisations deal with AI. We investigated 20 organisations in nine different industries and conducted semi-structured interviews, resulting in approximately

120,000 words of raw transcripts. We opted for a homogeneous group of interviewees, who shared several characteristics related to the research questions (DiCicco-Bloom and Crabtree 2006), such as having developed and implemented a human-facing chatbot. We interviewed eight organisations that implemented a chatbot, 11 software development companies that developed a chatbot (platform), and one marketing agency that assisted organisations wanting to implement a chatbot. The initial interviewees were approached via the personal connections of researchers and connecting with interviewees via LinkedIn. We chose conversational AI because it is a clear example of where AI and humans interact and there has been a public example of what can go wrong when AI is not developed correctly.

Semi-structured interviews offer a deeper understanding of a certain phenomenon than purely quantitative methods (Silverman 2000). The objective of the interviews was to explore the views, experiences and motivations of organisations in relation to AI (Gill et al. 2008). Performing qualitative research interviews enabled us to contribute to the literature based on the AI-related experiences of the interviewees, which is why the semi-structured interviews are the only data source for this qualitative research (DiCicco-Bloom and Crabtree 2006). In order to analyse the data, we applied a 'template approach' (DiCicco-Bloom and Crabtree 2006), as we reviewed and identified text segments within the transcripts using a template (categories) based on the above theoretical perspectives (Denzin and Lincoln 2011, Miller and Crabtree 1999). We used the text analysis software NVivo to support our data analysis and followed Burnard's (1991) method of analysing interview transcripts in qualitative research.

The coding process followed recommendations from Saldaña (2015) where a first round of pattern coding was done to find relevant themes to use in the analysis process. These codes then represent the higher level theoretical constructs present in the data (Saldaña 2015). To do so, we created a word cloud of the existing literature review and all corresponding articles using NVivo's word cloud functionality. This enabled us to extract 10 top level nodes, which provided a starting point for our analysis. This process was followed by a second method, eclectic coding, to find deeper and more complex meanings and themes in the data (Saldaña 2015), resulting in a total of 38 top level and sub level codes. Table 4 shows the 10 main themes and the 28 sub level themes found in the data. The results of the first and second cycle coding are presented in the following section of this paper.

Top Level Themes	**Sub level themes**				
Artificial intelligence					
Challenges					
Chatbot	Conversations	Costs	Development	Features	Success rate
	Monitoring	Personality	Reasons for development	Security	
Control Methods	AI	Analytics	Chatbot functionality	Code	Content
	Effectiveness	Learning of chatbot	Testing		
Data	Biased data	Training data			
Decision-making	During development	Post development			
Ethics	Ethical guidelines				
Future developments	AI in general	Changing organisations	Chatbots	Preventing damage	SAI
Governance					
Role of interviewee	Time in role				

Table 4: Codes

Results

We interviewed 20 organisations involved with developing a chatbot. There are multiple reasons for developing a chatbot, ranging from obtaining experience with AI to engaging with customers and improving marketing, as an on-boarding process, to increase sales or to reduce the number of staff required for customer support, or to free customer service staff for more complicated questions. There are different types of chatbots in use. So-called 'on rails' chatbots, where answers and questions are pre-defined, and more free-flow chatbots, where users can enter free text. In addition, there is the possibility to have the chatbots learn supervised or unsupervised, but the latter offers challenges as seen with *Tay*. As the Commercial Director of a large chatbot platform stated, 'conversational agents by itself do not necessarily have to be AI. AI can play into it. It's not necessarily a requirement for it'.

However, a key component of AI is data, as a German chatbot developer noted. Without data, it becomes difficult to build AI, which is especially true for conversational AI as a conversation, by its nature, is data driven (this is noted by the Commercial Director of an American chatbot developer). This data should be used ethically and in a legally compliant way to compute the data correctly so the chatbot does not end up misleading people by sharing incorrect results. Hence, data is important. The more data you can put in the entry, the better the experience will be from the outset, and the more advanced the chatbot can become, since AI requires training data. As a chatbot developer from Singapore in the hospitality sector states: 'What we do is, we collect, collect and collect and after that we input the data altogether and test the system based on that data and then we will keep iterating this process, rather than it learn on the go.'

When developing a chatbot, the best approach is to have AI and a person to work together until there is sufficient confidence around the decisions that are coming out of the system, because with data comes biased data (O'Neil 2016). There was a divide in how organisations treated biased data. Some organisations did not test data for bias and did not look for it, while others are confident that data is always biased. As a member of an Australian finance organisation said, ‘When humans are involved, bias is inherently going to make its way into chatbot systems’. Or as an American chatbot developer observed, ‘Bias is pretty hard to detect automatically. So, in the end of the day, you are going to need to pre-process that data’. It shows the importance of data governance (Begg and Caira 2012) as bias can affect the chatbot, as seen with *Tay*.

Since all conversations are data, it is possible to extract valuable information from the conversations, both actively and passively, to capture and feed that data into the overall reporting mechanisms. This is called conversational analytics; that is, what was said, how was it said, what was the intent, what is the sentiment, what was the goal, did we accomplish the goal, where does it fit in the larger context? Monitoring the conversations by analysing the transcripts is an important control method; such as, reviewing the transcripts and looking at places where the chatbot did not understand what people are asking and building up the datasets so it can be retrained. In addition, conversational analytics includes looking at places where the chatbot thinks it got it right, but was wrong, and with that the information can be rectified and conversations improved. Analytics can offer relevant training data.

Many of the organisations use transcript data from customer support or use data from chatbot conversations to further train the chatbot. To prevent problems such as seen with *Tay*, when developing a chatbot the rules for the chatbot need to be provided; that is, what it can do and cannot do, what the boundaries are, when wrong data is entered that could be deleted. Analytics can offer guidance and sentiment analytics can be used to judge if the chatbot user has a positive or a negative experience. Some organisations also use deep analytics to understand where customers have difficulties in the conversation and this enables the company to improve their service by tuning the approach to them. Further, there are third party analytics tools that offer insights in conversations and how the chatbot is used. However, some of these analytics tools are quite rudimentary and do not offer many insights. Therefore, some organisations developed their own analytics to monitor the chatbot, especially if a tailored approach, such as in the insurance industry, is required. Based on the analytics, organisations can detect the choke points of different users, where are they stuck, at which point they leave and stop using it and, based on other exit points, an organisation is able to identify problems.

Analytics is an important monitoring tool and most organisations measure metrics such as the number of impressions, how many times the chatbot opens, the number of unique people that visit the chatbot, the number of people that engage on the first, second, third or fourth question. KPIs are necessary to improve the process but should not become the main driver. As such, it is recommended to keep analytics separate from the experience of the chatbot. Within most organisations, the chatbot is feeding the analytics, but the analytics is not feeding the chatbot (as was the case with *Tay*). It is really supervised learning, but as the chatbot needs to be live 24/7, curation and monitoring should, therefore, be done in real-time. How the chatbot learns is an important aspect to determine the success of the chatbot. *Tay* used unsupervised learning, where the data of the users was used to learn (Alaieri and Vellino 2017). This technology is new and, hence, none of the organisations apply unsupervised learning or let the chatbot learn by itself based on the input of the users. Some follow an on rails chatbot, which has very limited freedom in terms of users' input. Others allow more free text input, but they use a supervised learning strategy where humans control what the chatbot learns from the conversations. In this way, situations such as *Tay* are prevented. In conversations, context matters. As an American chatbot developer states: ‘You got to have rules that govern the learning process itself. There has to be an iterative semi-supervised process teaching it how to identify things.’ All organisations manually assist the learning, trying to point it in the right direction. As such, ‘machine learning requires a lot of man work,’ states a chatbot and a software developer from Lithuania. Every step of the way has been augmented or verified by humans. As many people as possible should play with the bot as if they were real users. This ensures having a very rapid feedback and learning and prototyping loop. Many organisations try to break a chatbot before going live; this testing process helps to identify bugs with the AI.

For these reasons, many organisations first start with a frequently asked questions (FAQ) chatbot, which is a chatbot on rails that does not offer any free text. From that, organisations added machine learning capabilities to make the bot smarter and enable it to deal with more complex questions. Eventually, one American chatbot developer created a chatbot that is person-aware; meaning the chatbot knows who the person is in the chat, as the chatbot is linked to internal systems. As a result, it is a lot smarter because it has a better understanding of the context. Yet in the end, a chatbot should never try to trick the user that they are human. When developing a chatbot for an organisation, a limited and focused scope, that alleviates a pain point, is recommended. Those expectations should be clear from the user’s perspective and from the company’s perspective at the outset. Chatbots themselves, without any integration, provide limited value.

Sentiment analysis helps ensure the chatbot has a positive attitude and the customers have a positive experience. The use of profanities is a serious problem for organisations and chatbots, as is not responding to profanities in a provocative way or way that can be bad for publicity. People always try to break a chatbot by inputting nasty comments. An Australian chatbot developer had to block a 14-year-old child because he threatened to kill the chatbot.

Central to a positive experience is an overarching set of rules that drive the conversation and determine what the chatbot can and cannot do. To ensure a positive customer experience, some organisations implemented a simple flow to move the chat from the chatbot to a live agent. An Australian finance organisation implemented a system where, if the chatbot did not understand what it was being asked or did not understand the intent, there was an option to transfer to a live agent and continue servicing the customers. The live agent would get access to the chat history. Not all questions can be answered, so the most important part of the chatbot is to actually show the expectations that it cannot do everything.

Control Methods

Many of the organisations interviewed face numerous inflammatory and derogatory comments on their social media channel, including the chatbot. If the chatbot is not trained properly, problems such as *Tay* could happen more often. Therefore, organisations recommend taking a conservative approach and keeping the chatbot assisted and within range, so it can be controlled. This is where curation and ethics come in, as the danger is when a chatbot does not understand what a user is trying to ask. 'Ethics is a tough one', said the project manager of an Australian finance company. Thus, AI needs to have content that can be classified as a 'no-go' zone. It needs to have a list of content and topics it cannot talk about, even if users harass and try to break it. When users talk about those things, it should revert automatically to something else and have a positive sentiment instead. Therefore, it is important to analyse all the conversations and learn from them, especially when working with free text, which is all about parsing it in the right way and determining the probability of a certain intent. The higher the minimum probability, the more risk-averse that chatbot becomes. As such, AI has to tell you clearly what it can do and what it cannot do. This is a predecessor of XAI, but a lot easier to achieve. ‘I am a chatbot, I'm a virtual assistant who is an expert in 10 things, but not 11. And when you get to the 11th, you have to be willing to learn and within certain parameters’, observes an American chatbot developer.

Most of the organisations interviewed developed their chatbot using an agile development methodology, allowing them to remain flexible and iterate quickly. As a result, decisions were often made ‘on the fly’, and only large corporates such as the financial services organisations had an official governance structure in place, including a steering committee. Instead, often problems were solved on the go, allowing the development to move quickly and avoid the delays often involved with software development (Ewusi-Mensah 2003).

There are two types of monitoring that is executed by the organisations:

1. Ensuring that the chatbot works, so pinging the service to know that the chatbot is live. This is related to the technical aspects of the chatbot, the code. Monitoring the server logs and the event logs and provide live notifications if something goes wrong.
2. Monitoring the conversation to see how the chatbot responds and in case it does not know an answer or if there is unexpected language by

the user or the chatbot. This can then be used to improve the conversation through supervised learning.

To control AI, a hands-on approach is needed, as stated by the founder of a chatbot platform for the food industry. You need to make a significant investment to make sure it works properly. If you don't do that, it can bring a lot of damage, according to an Australian government organisation. After all, you cannot have a machine think like a person. Understand the strengths and maximise those advantages. The best outcome is when humans and machines work together as opposed to apart, according to the manager of an Australian government organisation.

Most of the organisations also tested the code, although not all. Especially chatbot developers have rigorous testing practices in place and are confident those practices are effective. These processes include a testing environment, an acceptance environment and a live environment to ensure everything can be properly tested before going live. However, many organisations did not test the third-party tools they were implementing and instead trusted the third party that their tool and the code in that tool were correct and did not have any bugs. There is a strong reliance on and confidence in third party tools. However, it is important to have proper controls in place. One American chatbot developer went as far as to prohibit third party developers from accessing the code.

However, bugs will always come through, as that is the nature of software development, as an American chatbot developer conveys. One English chatbot developer for the insurance industry went even further. They work with such big clients that they require thorough testing by their governance framework and as such, require penetration tests on the system as well, carried out by a third party.

Future of AI

There is a divide in how people see the future of AI. Some interviewees do not see robots taking over in the next 100 years, while others believe it will happen in the next few years. However, the most important thing with AI is data (O'Neil 2016) and according to the interviewees, there are going to be many more missteps than successes. It is all about how data is applied within the AI, because ultimately no single machine learning algorithm is ever going to be the best at anything. ‘It's about building systems of systems and training small bits that become parts of larger bits […] AI is more like a box of Lego, meaning different algorithms doing different things in different ways to solve a problem’, according to a Commercial Director of an American chatbot developer. Increasingly, humans and AI will be working together, augmenting humans and removing the mundane tasks. The paradox is that, as a Dutch CEO of a chatbot development company expects, AI will make organisations more humane, instead of more robotic, because in many cases people are now performing actions that can easily be done by a robot; freeing them up will enable them to become more customer-focused.

Machine learning has huge risks, so extensive testing and governance processes are required. Stakeholder management and re-evaluation by those stakeholders to determine whether it is on track or not and pull it or tighten the parameters around it if it is not, are important when dealing with AI, according to an Australian cultural institution. In the end, AI can offer a lot of benefits to humanity, but it requires the right regulation and control methods to prevent bad actors from creating bad AI.

Controlling AI has become an important topic of discussion in both the academic and business worlds (Russell, Dewey, and Tegmark 2015, Anderson 2015b, Alfonseca et al. 2016), and with this paper we aim to offer lessons for governance that can be applied in management literature as well as by practitioners. As the example of *Tay* shows, even conversational AI can be harmful if it is developed in the wrong way and misses some of the control methods that many of the interviewed organisations applied. As such, Responsible AI is ultimately a governance question. Therefore, the objective of this paper is to see if lessons learned from this qualitative research on conversational AI can also be applied to AI in general and, with that, contribute to developing Responsible AI. In the next section, we discuss the implications of our research for governance practices both in management literature as well as for practitioners.

Implications for Governance Practice

None of the researched organisations developing conversational AI are involved with incorporating either XAI or machine ethics in their chatbot developments. This could be because XAI is a new suite of machine learning techniques that is still highly challenging (Gunning 2017), while instilling ethics into AI is even more difficult (Bostrom and Yudkowsky 2014). Hence, it is not surprising that these organisations have not incorporated these concepts into their AI developments, especially since ‘the understanding of AI internally is quite low’, as the Digital Engagement Manager of an Australian cultural institution mentioned. Therefore, we focus on the control methods suggested by Bostrom (2014), as the research provided valuable insights into the governance practices organisations implemented to ensure the chatbots worked correctly, such as implementing extensive testing practices and preventing unsupervised learning of the chatbots. To understand how these practices would affect agency theory, we return to the controlling, monitoring and supervising mechanisms already applied in organisations to solve the principal–agent problem when dealing with humans, and we adapt them to artificial agents. Therefore, based on our research of 20 organisations that developed conversational AI, our contribution lies in expanding existing agency theory (see Table 5) to include AI agents as well:

Control

Our research revealed that organisations already take measures to control AI. While these might not be the technical measures Bostrom (2014) suggest, such as including a 'kill switch', they do assist in controlling the agent to ensure it works as intended. Control methods include code testing in various digital environments, such as a staging and acceptance environment, before the AI is deployed to a live environment. Humble and Farley (2010) refer to this as a 'continuous delivery' process, where building, integrating and testing environments assist in minimising bugs when deploying software. Apart from testing the code, it covers including an overarching rule-set that drives the actions of the algorithm, or in this case the conversation. As the Commercial Director of an American chatbot platform explained, 'You need to have an overarching rule-set that drives your conversation, you want to be able to apply at a given point to the conversation, the need, the requirement to identify the intent and then figure out what information needs to be extracted from that intent-model.' Including such an overarching rule-set allows the principal to direct the actions of the machine (Vladeck 2014, Holland 1992). A third control method is that of limiting AI to one specific task and then combining different AI's to build a system, which the Commercial Director of an American chatbot platform refers to as 'AI is like Lego'. Finally, multiple interviewees mentioned the need for AI regulations to control AI developments, like Elon Musk's OpenAI calls for. Together, these four control methods will assist in ensuring the agent (the AI), will act as intended by the principal (the developer, manager or organisation).

Monitoring

While monitoring human agents is done through evaluating performance and strategy implementation, monitoring digital agents can be done using analytics. Analytics refers to using data sources and statistical methods to understand how a digital agent performs (Chen, Sain, and Guo 2012, Chui et al. 2011) and obtain insights about what has happened (Mortenson, Doherty, and Robinson 2015). There are a wide variety of analytics, of which conversation analytics (the analytics capability to analyse user conversations (Mei et al. 2015) and sentiment analytics (the analytics capability to identify, extract and quantify subjective information to detect emotions) (Stone, Dunphy, and Smith 1966)) are most relevant for chatbots. Using such analytics, organisations can better understand the context (Van Rijmenam et al. 2018) and identify problems such as where users are stuck, where the chatbot cannot respond, and when users leave. Analytics offer insights to improve the AI and using subsequent analytics, the principal can see if the problem has indeed been solved. As such, analytics is an important monitoring tool (Baesens et al. 2014).

Supervising

Coaching, mentoring and steering a digital agent can be done by feeding the insights from analytics back into the algorithm and using unbiased training data to train the AI. Such supervised learning, whereby a human agent controls the data that is used to train the AI, can help the AI learn. Unsupervised learning, whereby the AI learns using unfiltered input data, as was the case with *Tay*, can have unwanted consequences (Hastie, Tibshirani, and Friedman 2009). Preventing unsupervised learning can, therefore, contribute to solving the principal–agent problem as the input data is pre-processed, cleansed and any bias should have been removed (O'Neil 2016), thereby steering the AI in the right direction.

Agency Theory	**Management**	**AI**
Control	Strategic and financial control methods (Baysinger and Hoskisson 1990, Hoskisson, Hitt, and Hill 1993, Ravenscraft 1996, Gupta 1987)	Applying control methods such as code testing, ensuring an overarching rule-set that drives conversations, limiting AI to one specific task and developing AI regulations.
Monitoring	Monitoring activities such as succession planning, monitoring strategy implementation and evaluation and rewarding of C-level executives (Rindova 1999, Pitcher, Chreim, and Kisfalvi 2000, Conyon and Peck 1998, Boyd 1994, Hillman and Dalziel 2003)	Analytics such as conversation analytics or sentiment analysis to understand where improvements are required.
Supervision	Coaching, mentoring or even steering of the agent (Strebel 2004, Christen, Iyer, and Soberman 2006, Hilb 2008)	Feeding analytics and unbiased training data back into the system using supervised learning.

Table 5: Agency theory and artificial agents

Controlling, monitoring and supervising seem a suitable approach for developers, managers or organisations to reduce the effects of the principal–agent problem when dealing with AI. They will not likely solve the principal–agent problem, just like controlling, monitoring and supervising does not solve the principal–agent problem when dealing with human agents. However, as software will always have bugs, our research shows that problems with such digital agents can be reduced with the right governance practices.

Limitations and Further Research

Our research focused on conversational AI, but conversational AI is only one type of AI. Although any AI is ultimately software, and software has bugs, the control methods that worked for the organisations we interviewed might not suffice for different types of AI. Since our research only interviewed organisations that developed or implemented a chatbot, the outcome of this research might not completely apply to all other types of AI. To determine the most effective control methods for any type of AI, more research is required. In addition, none of the organisations we interviewed had experience with XAI or machine ethics. Hence, we were not able to offer insights on those topics.

Research around Responsible AI is still in its infancy and substantial additional research is required to understand what governance practices would work best in which situation. Since this research did not include a technical analysis of all the chatbots developed by the organisations interviewed, we were unable to find dependencies or causalities on the control methods applied and the number of bugs found in the AI. Therefore, more research is required not only in organisations that have developed chatbots, but with any organisation that has developed any type of AI. This would likely also include longitudinal studies to see whether the AI continues to behave over time, even if it comes across data it has not been trained on.

Conclusion

Artificial agents are rapidly becoming more intelligent and it is a matter of time before AI will surpass human intelligence. Therefore, it is important to develop an effective set of preconditions, control methods and ethical guidelines in the coming years to ensure a proper transition from a human intelligence driven society to an AI driven society. If we get it right, an abundant future lies ahead; if we get it wrong, it could result in an existential crisis. Therefore, preparing organisations, societies and individuals for these tasks will give us a better chance in the years from now when we are on the breach of an intelligence explosion. The governance practices, including controlling, monitoring and supervising digital agents, will likely contribute positively towards solving the principal–agent problem when dealing with AI. Therefore, we should prevent social silence as happened with the financial crisis (Tett 2009), costing us billions of dollars, as bad (S)AI could cost us the planet. Although nothing is certain when dealing with AI, as Turing (1950, 460) already concluded: ‘we can only see a short distance ahead, but we can see plenty there that needs to be done’.

Chapter 5: Discussion

With change happening faster than ever before (Hajkowicz et al. 2016), it can be said that we live in exponential times. Increasingly, organisations have to be able to respond to disruptions in their uncertain and ambiguous environment. Organisations wanting to endure competitive advantage in such environments have to emphasise excellence in day-to-day business operations and detect, anticipate, and respond to disruptive changes (De Meyer, Loch, and Pich 2002, Petrick and Martinelli 2012) while displaying industry leadership and managing shifting behaviours of stakeholders (Buysse and Verbeke 2003). Such 'organisational ambidexterity' (O Reilly and Tushman 2004, Raisch et al. 2009) is especially important when facing environmental ambiguity or deep uncertainty (Teece, Peteraf, and Leih 2016, Bennett and Lemoine 2014). For organisations to achieve this ambidexterity, it is recommended to rely on data as a key resource for their business and develop data-driven business models (Hartmann et al. 2016). This includes processing, analysing and visualising a variety of internal and external data sources and use the insights derived from the data to create new products and services, and to connect with the right customers at the right moment (Hartmann et al. 2016). For many organisations, this requires changing their mindset, as a great deal of organisations still base their decisions on experience and intuition instead of data (analytics) (Khatri and Ng 2000, PWC 2015). Therefore, when organisations turn existing analogue processes into digital processes they can be analysed and used to create a digital platform to grow the business (Gurbaxani 2016).

My research confirms this and suggests that EITs do indeed change the interaction among organisations and technologies. Descriptive and predictive analytics can be applied to sense and seize opportunities; peer-to-peer transactions allow actors to self-organise and create value; and increasingly intelligent AI requires renewed governance practices to prevent AI from inflicting any damage on those actors involved. Doing so will change existing strategic management practices by improving and automating decision-making capabilities; change organisation design by incorporating cryptography, consensus mechanisms and smart contracts to ensure trust among decentralised actors; and require different governance practices to control, monitor and supervise artificial intelligent actors. Making data the heart of the organisation will allow for new types of interactions, resulting in changes to existing collaboration practices.

For years, contemporary tech startups have valued the possibility of collecting and analysing data to create new organisations that are more agile and flexible than existing ones (Croll and Yoskovitz 2013). Thanks to the growing availability of advanced technology, many of these new digital platform organisations (Romero and Molina 2011) are copying highly successful companies where data is at the core of the business (Davis 2015). Within these organisations, there is an increased importance of data governance due to extensive sharing of data and processes across organisational boundaries, as well as the delicate balances between generativity and control (Yoo et al. 2012). This balance between power and empowerment seems to be shifting within these new data-driven platform organisations (Grossman 2016) and consequently this creates a shift in collaboration among the actors involved, by including previously excluded actors, as well as by moving from pure human-to-human interactions to human-to-machine interactions and increasingly even machine-to-machine interactions (Swan 2015b, Tsvetkova et al. 2017). As a result, organisations are faced with new ways of collaboration to enable their strategic management choices. This requires a different mindset within organisations as they need to rethink internal processes and structures to enable these new ways of cooperation among those actors (human and artificial) involved (Hoc 2000) to ensure continued productivity growth (Schuh et al. 2014). Such organisations not only enable new revenue streams and continuous growth opportunities, they also create new partnerships with previously excluded partners. Snow et al. (2011) refer to this as collaborative communities, where organisations that want to succeed will have to share knowledge and engage in collaborative relationships with industry partners to drive innovation, enabled by data and data related technologies (Kitchin 2014).

Each of the EITs discussed in this thesis affects the organisation differently and changes collaboration among actors in distinct ways. To understand the contribution of my thesis, the following sections discuss the effects of big data analytics, blockchain and AI on strategic management, organisation design and governance, and provide insights into how I believe it will change collaboration among those actors involved.

5.1 Big data analytics and strategic management

In the first paper, I set out to investigate how organisations can apply big data analytics in dealing with ambiguity and uncertainty. Although big data refers to the creation, storage and usage of large volumes of data (Laney 2001), big data analytics offers insights from any type of data, regardless of the volume, velocity or variety. The various types of big data analytics enable organisations to detect, anticipate and respond strategically in ambiguous and uncertain business environment (Vahn 2014, Evans and Lindner 2012, Kaisler et al. 2013, Delen and Demirkan 2013, LaValle et al. 2011, Larson and Chang 2016). By doing so, big data analytics changes how organisations are managed, how organisations are designed, their culture and identity, and how decisions are made (Brown 2008, George, Haas, and Pentland 2014). While early on, some practitioners and scholars challenged the potential of big data analytics (Bollier and Firestone 2010), today, for many businesses, the most likely path to creating competitive advantage is by using big data and subjecting it to (advanced) analytics (Barton and Court 2012), turning primary data into valuable insights (Chen, Sain, and Guo 2012, Chui et al. 2011, Mortenson, Doherty, and Robinson 2015). These types of analytics include descriptive analytics, providing insights into what happened; predictive analytics, allowing organisations to make future projections based on historical and present data (Gandomi and Haider 2015); and prescriptive analytics, which leverages machine learning, simulations and mathematical optimisation to help enterprise leaders make better-informed decisions (Delen and Demirkan 2013). As the first paper showed, descriptive and predictive analytics serve as the analytical framework that Teece (2007) refers to as being required to achieve a competitive advantage in ambiguous and uncertain environments. As such, organisations can apply descriptive analytics to better sense the environment and apply prescriptive analytics to seize opportunities by offering insights that improve an organisation's decision-making capabilities.

Access to such knowledge and information not only results in a better understanding of the context and improved decision-making capabilities, but also results in a shift in power within organisations (Grossman and Siegel 2014, Berner, Graupner, and Maedche 2014, Galbraith 2014b). Traditionally, the power to make (strategic) decisions within organisations resided with those leaders who had the most experience and were on top of the hierarchy. Leaders have the power to make decisions because they have access to limited, tangible resources and knowledge not available anywhere else in the organisation. After all, knowledge is a form of power and knowledge can be gained from power (Foucault 1977). However, when data and insights from data are widely accessible in real time, the balance of power changes, moving it away from leaders with years of experience to whoever has access to data and has the power to analyse that data for insights to make (strategic) decisions and create new opportunities (Grossman and Siegel 2014, Berner, Graupner, and Maedche 2014, Galbraith 2014b). When more people have access to knowledge, empowerment is a possibility (Foucault 1977). Thus, when organisations provide more people access to knowledge, through big data analytics, power is distributed more equally, enabling empowerment within an organisation and resulting in decentralised decision making among employees and customers (Galbraith 2014b, Fosso Wamba et al. 2015, Apte, Dietrich, and Fleming 2012, Berner, Graupner, and Maedche 2014). Organisations that empower their employees and customers, and partner with previously excluded actors, whether human or machine, are less likely to be surprised by changes in the environment (Teece, Pisano, and Shuen 1997b, Teece 2007). Therefore, increasingly organisations adopt an open strategy approach, which is the decentralisation of strategy formulation across previously excluded, internal and external actors (Chesbrough and Appleyard 2007). An open strategy is possible thanks to big data analytics, and it significantly changes how organisational stakeholders interact with each other.

5.1.1 Big data analytics and open strategy

Traditionally, organisations focused on ownership and control of (in)tangible assets to achieve competitive advantage. However, ownership of resources is no longer vital for success (Chesbrough and Appleyard 2007). Knowledge; that is, data, is widespread due to the rise of new technologies and this can be used to fuel innovation. Embracing external ideas and knowledge and combining it with internal research and development will enable organisations to create new business models and opportunities (Chesbrough 2006) and remain competitive in a digital age. Collaborating with new actors increasingly gains acceptance, thanks to the plummeting costs of communication (Chesbrough and Appleyard 2007, Appleyard and Chesbrough 2016) and the availability of digital artefacts. These enable organisations to use the intelligence of the crowd to create better solutions, improve innovation and make better decisions (Surowiecki 2005, Stieger et al. 2012a).

Open strategy is an extension of open innovation (Whittington, Cailluet, and Yakis-Douglas 2011). Open innovation focuses on discovering, exploring and exploiting innovation opportunities through multiple internal and external resources resulting in new products and services (Chesbrough 2003, Dobusch, Seidl, and Werle 2015). However, open strategy embraces the advantages of an open approach to creating value instead of raising barriers (Chesbrough and Appleyard 2007). It uses open innovation to collectively create new ideas and perform strategy making activities (Dobusch, Seidl, and Werle 2015). Open strategy enables organisations to respond to ambiguous and uncertain environments as it offers flexibility, speed of innovation and new strategic opportunities, resulting in new ideas, products and services due to access to different, internal and external, data sources (Dittrich and Duysters 2007, Chesbrough and Appleyard 2007).

Open strategising consists of two important principles: inclusiveness and transparency (Amrollahi and Ghapnchi 2016). Inclusiveness is about involving previously excluded actors in the strategy making process (Dobusch, Seidl, and Werle 2015, Pittz and Adler 2016, Amrollahi and Ghapnchi 2016, Kennedy, Whiteman, and van den Ende 2016, Appleyard and Chesbrough 2016), while transparency is about being transparent when communicating with those actors (Amrollahi and Ghapnchi 2016, Appleyard and Chesbrough 2016, Gegenhuber and Dobusch 2017, Pittz and Adler 2016). Both principles are only possible because of the availability of data and data related technologies, as it enables organisations to actively incorporate input from previously excluded actors during strategy making (Pittz and Adler 2016) who must actively engage and interact with each other, since sensemaking 'takes place in interactive talk' (Taylor and Van Every 1999, 58). Within collaborative decision making, transparency and inclusiveness are, therefore, important. Transparency ensures all actors remain aligned, while inclusiveness ensures actors can actively participate in decision-making processes (Pittz and Adler 2016).

Although open strategising changes collaboration within human-to-human networks by empowering employees and customers (Korsgaard, Schweiger, and Sapienza 1995, Mantere and Vaara 2008), it can also result in an extra burden of work (Hautz, Seidl, and Whittington 2017) due to the need to digest large amounts of information (Luedicke et al. 2017, Stieger et al. 2012b), which is where big data analytics comes in. Big data enables inclusiveness by collecting and aggregating ideas, while analytics enables transparency by summarising the conversations and detecting actionable ideas among the data, using NLP and text analytics, which can result in new business lines or strategic directions for the organisation (Powley et al. 2004, Bjelland and Wood 2008, Johnson et al. 2010, Whittington, Cailluet, and Yakis-Douglas 2011, Lewin, Välikangas, and Chen 2017).

Not only does big data analytics offer the insights to better interpret the fast-changing environment and improve the decision-making capabilities, it also changes how *the social* collaborates when organising activities, enabled by *the material* and *the artificial*. Though open strategising is one form of collaboration made possible due to data and data related technologies, there are more forms of collaboration that organisations should be aware of in these changing times, especially when *the social* and *the material* become involved with blockchain and AI.

5.2 Blockchain and organisation design

Apart from collecting and analysing data to achieve competitive advantage, collaborating with industry partners can also result in a competitive advantage (Snow et al. 2011). With the development of blockchain, doing so has become easier than ever before. Blockchain, the distributed ledger technology first conceived by Nakamoto (2008), has evolved significantly in the past few years. It uses database technology to store and indefinitely keep an ever-growing list of data records (Lemieux and Lomas 2016, Chaum 1985, Nakamoto 2008). The characteristics of an immutable, verifiable and traceable decentralised ledger (Umeh 2016, Mattila 2016, Lemieux and Lomas 2016) result in new forms of organisation design. It has resulted in *decentralised* organisations where trust is created through cryptography among actors that are dispersed and decentralised (Davidson, De Filippi, and Potts 2016). It also enables *autonomous* organisations, where decision making is automated using smart contracts (Swan 2015b, Davidson, De Filippi, and Potts 2016) and governance is embedded in the code (Shrier, Wu, and Pentland 2016). A decentralised organisation does not have to be autonomous but an autonomous organisation has to be decentralised. Organisations that are *decentralised* and/or *autonomous* are enabled by peer-to-peer transactions within human-to-human and human-to-machine or even machine-to-machine networks. Where the two come together, in *DAOs*, complex mechanisms interact to organise activity automatically and autonomously, without management or employees (Garrod 2016). These new disruptive forms of organisation design rely heavily on a delegative leadership style and advanced IT to enable dispersed teams to collaborate without a centralised power that makes the decisions, making them a potential threat to incumbents (Mendling et al. 2018, Tapscott and Tapscott 2017). Blockchain requires collaboration outside the boundaries of organisations (Michelman 2017), resulting in organisations where peer-to-peer collaborations thrive and industry stakeholders are fully interwoven as one cannot exist without the other.

However, peer-to-peer collaboration, or networking, is nothing new and has been around since the launch of the web. The most well-known example is (torrent) file sharing (Schollmeier 2001, Barkai 2001), which has predominantly been used to share content among consumers, including illegal content as well as viruses and spam (Damiani et al. 2002, Pouwelse et al. 2004). It has contributed significantly to the growth in copyright infringements across the globe (Goel, Miesing, and Chandra 2010). However, since the development of Bitcoin and its underlying blockchain technology (Nakamoto 2008), peer-to-peer networking is experiencing increased adoption across industries, this time also for the better (Van Rijmenam and Ryan 2019). Blockchain-enabled peer-to-peer collaboration among humans and/or machines has resulted in intermediary-free transactions (Swan 2015b), which opens up a great deal of benefits for organisations (Zamani and Giaglis 2018). Removing the middle-men changes how actors interact and collaborate (Christidis and Devetsikiotis 2016). Within such networks, smart contracts enable actors (human and/or artificial) to collaborate and perform transactions that will execute automatically once certain pre-set conditions have been met (Morini 2016, Luu et al. 2016). As such, they will directly affect social contracts within society and within organisations, since it removes the need for human judgement when actors collaborate (Buterin 2014, Swan

2015b). Although the organisation design research in the field of blockchain is limited, technical scholars have shown that blockchain enables efficient and effective peer-to-peer, human-to-machine and machine-to-machine interactions (Zamani and Giaglis 2018, Sikorski, Haughton, and Kraft 2017, Xu et al. 2016, Bahga and Madisetti 2016). Trustless, peer-to-peer collaboration among humans and/or machines, where (strategic) decision making is automated and governance is embedded in the code, is a true paradigm shift (Swan 2015b). For the first time, machines can collaborate automatically and even autonomously with other machines and even humans, while ensuring the outcome aligns with what has been already agreed upon. Humans develop the decentralised and/or autonomous organisation, which will then interact with human and artificial actors, possibly even autonomously. As such, thanks to blockchain technology, organisations and technology become increasingly interwoven. However, the more they do so and the more human-to-machine and machine-to-machine collaboration becomes pervasive, the more organisations will need AI to govern these interactions, which in itself requires governance.

5.3 Artificial intelligence and governance

AI is intelligence presented by machines that perceive its environment and take action accordingly, to maximise its ultimate goal (Bostrom 2014, Russell and Norvig 1995). To ensure this is done responsibly and no harm comes to those actors involved, organisations should incorporate governance practices that involve controlling, monitoring and supervising AI. The principal–agent problem when dealing with artificial actors can be overcome by thoroughly testing the code of AI; by analysing the behaviour of the artificial intelligent actor; and by supervising its learning abilities. Such governance practices are becoming increasingly important when dealing with artificial actors to prevent biased algorithms causing any damage (O'Neil 2016). Especially, because the continuous stream of breakthroughs of AI, made possible through increased ‘computational capabilities, algorithm design and communication technology’ (Alfonseca et al. 2016, 1), results in algorithmic businesses that rely on complex algorithms to automate business processes and decision making (Prentice 2016). Since it is considered a natural evolution of any transformation to a data-driven organisation, whereby new value can be created thanks to AI (Prentice 2016), algorithms are likely to take over jobs, resulting in significant loss of jobs across the globe and are, therefore, increasingly observed as a risk to society (Ford 2015, Hawksworth 2018, Furman 2016, Turchin and Denkenberger 2018). This is why developing responsible AI is also rapidly increasing in importance (Muehlhauser and Bostrom 2014).

When discussing AI, it is crucial to understand the distinction between different forms of AI: Narrow Artificial Intelligence (NAI), Artificial General Intelligence (AGI) and Super Artificial Intelligence (SAI) (Bostrom 2014). NAI refers to AI that is more intelligent than humans on specific tasks in relatively narrow domains (Baum, Goertzel, and Goertzel 2011). AGI refers to AI systems having autonomous self-control and self-understanding, and the ability to learn new things to solve a wide variety of problems in different contexts (Goertzel and Pennachin 2007). The final phase of intelligence is SAI, which means intelligence that far exceeds that of any person, however clever (Bostrom 2014, Good 1966). SAI could result in new forms of intelligence unfamiliar to humankind today (Armstrong, Sandberg, and Bostrom 2012, Bostrom 2014). With AI being fundamentally different from human intelligence (Ayoub and Payne 2016), a different approach to governance is required.

The increasing convergence of the human and the machine thanks to AI (Norman 2017), results in social, technological, political and ethical implications where AI and humans are becoming increasingly interwoven in mutually dependent networks (Fleischmann 2009). Within these human-machine networks, both artificial and non-artificial agents interact in the same context; for example, when dealing with conversational AI (also known as chatbots). Chatbots are a tangible example, and one of the most widely used, where humans and machines work together to achieve a goal (Dale 2016, Reshmi and Balakrishnan 2018). A chatbot is a communication interface that uses NLP and AI to comprehend human language and perform tasks or services for a user (Reshmi and Balakrishnan 2018). Even chatbots are not without risk, as evidenced by the example of Twitter bot Tay developed by Microsoft (Schlesinger, O'Hara, and Taylor 2018).

Therefore, developing human-machine networks consisting of artificial intelligent actors requires a deep understanding of how AI works and how it can behave ethically (Goldsmith and Burton 2017), which is highly challenging (Bostrom and Yudkowsky 2014) and an upcoming research field (Satell 2016, Anderson and Anderson 2011). However, AI not only results in increased human-machine interactions, but also in abundant machine-machine interactions that evolve as dynamic technological-cultural structures (Boyd and Holton 2017, Dourish and Bell 2011, Šabanović 2014). Both human-machine and machine-machine networks consisting of advanced AI require human adaptation (Boyd and Holton 2017), especially when AI, or humans, behave unexpectedly. Already, this is happening in AI-only networks, where algorithms start competing against each other (Leibo et al. 2017), develop new encryption methods (Abadi and Andersen 2016) or create their own secret language, unsolicited (Lewis et al. 2017), but it also happens in human-machine networks where malicious developers used AI to create so-called 'DeepFakes' to deceive the masses (Wang, Angarita, and Renna 2018, Buccafusco, Grubow, and Postman 2018). Therefore, multiple watchdog groups, such as the Future of Humanity Institute and OpenAI, recently warned for the malicious use of AI and called for action on policymakers, researchers and engineers (Brundage et al. 2018).

Behaviour of human and artificial actors changes when interacting in human-machine or machine-machine networks. Therefore, incorporating governance practices such as controlling, monitoring or supervising both human and artificial actors can contribute to preventing AI from harming others, whether initiated by human or artificial actors. As such, *the social* can govern *the artificial* to ensure that AI does not harm actors involved but results in a sustained competitive advantage for the organisation.

5.4 Data-driven organisations

As Gurbaxani (2016) argues, every company should think like a software company and to do so, my research suggests to apply descriptive and predictive analytics to understand the context of the organisation and to improve decision-making capabilities by interpreting different signals. In addition, blockchain can be incorporated to decentralise the organisation by implementing cryptography to create trust among actors involved and move to an autonomous structure by automating decision making using smart contracts and embedding governance in the code. However, when also incorporating AI, it requires new governance practices that cannot be embedded in the code, but instead involve thoroughly testing the code of AI, analysing the behaviour of the artificial intelligent actor and by supervising its learning abilities. Organisations could incorporate one or multiple EITs within their organisation. They can use them separately or integrate them within one another. The more these technologies converge, the more an organisation is likely to become a data organisation, regardless of the product or service that the organisation offers. However, integrating multiple EITs could have consequences on how the organisation is managed and any implications of that will require further research.

Companies such as Google, Facebook, WeChat or Amazon are popular examples of organisations that have long understood this paradigm shift and have collected data rigorously since their inception. These organisations use technology to facilitate collaboration between stakeholders and where human-to-human interactions are increasingly replaced with human-to-machine and even machine-to-machine types of interactions. With more organisations slowly also understanding the need to become a data company, organisations in the not too distant future will become involved in numerous interactions among humans and machines, resulting in complex strategies and unexpected technical, ethical and social implications. EITs indeed seem to change how the social, the material and the artificial interact. As such, the key argument underlying this research project is that organisations that are most capable of incorporating big data analytics, blockchain and AI will stand the best chance to remain competitive in this data-driven future.

5.4.1 A critical note on data-driven organisations

The key thesis underlying this research project is that data-driven organisations that incorporate big data analytics, blockchain and AI will experience a change how they organise activities within organisations. These organisations datafy their processes, distribute their data via the cloud or using distributed ledger technologies, analyse their data using descriptive or predictive analytics to sense and seize opportunities and automate their decision making using AI. Currently, data-driven organisations cannot function without humans in the loop (Anderson 2015a) as organisations remain social entities (Daft, Murphy, and Willmott 2010). This changes when organisations turn into a DAO. However, almost certainly, most of the existing organisations will never transform into a DAO, which is absent of management and employees and run completely by autonomous code. Consequently, there remains a human element to organisations and as a result *the social*, *the material* and *the artificial* should exist in coherence and interact with each other without negatively affecting one another. This means the artificial adheres to the ethics valued by the social, the material is bound by the norms and principles of our society and the culture within an organisation and the social is not subordinate to the material and the artificial. All three should exist in balance with each other, and organisations that ignore the human-side of doing business are likely to face difficulties.

5.5 Research implications and contributions

The overall theoretical contribution of this research is related to obtaining a better understanding how big data analytics, blockchain and AI will affect organisation design, strategic management and governance, as well as how it changes collaboration among those actors involved. With sociomateriality theory as the theoretical lens for this research, I have explored the theoretical issues related to EIT and presented a new understanding of the relationships between the social, material and artificial, thereby expanding the current theory on sociomateriality and preparing it for the EIT age.

Each of the EITs discussed in this thesis moves through a common cycle, from an innovation trigger, to the peak of inflated expectations, and through disillusionment before reaching the slope of enlightenment and plateau of productivity (Walker 2017). While big data analytics may have reached the plateau of productivity by becoming a pre-requisite for competitive advantage (Barton and Court 2012, Wamba et al. 2017, Gupta and George 2016, Akter et al. 2016, LaValle et al. 2011, Kamioka, Hosoya, and Tapanainen 2017), this certainly is not the case for blockchain and AI, which still reside at the peak of inflated expectations (Walker 2017). Consequently, while research on big data analytics is plentiful, as demonstrated in the meta-synthesis done in the first study, research on the strategic and organisational implications of blockchain and AI remains limited. With this thesis, it was my objective to contribute to this research field and offer a unique perspective by combining the three technologies, something that had not yet been done by (management) scholars, to understand how they will affect the organisations of tomorrow.

5.5.1 Theoretical contribution

The first study contributes to increasing our understanding of big data analytics as a dynamic capability that enables management to understand their environment better and improve processes and decision-making capabilities (the social). To understand changes in the environment, Teece (2007, 2012) suggests dynamic capabilities require 'some kind of analytical framework' (Teece 2007, P1324) to better understand and develop dynamic capabilities. With this study, I expanded this notion and clarified that the analytical framework should consist of descriptive and predictive analytics to more clearly understand the fast-changing environment and improve decision-making capabilities. As such, big data analytics can be considered a generally dynamic capability that supports management in times of ambiguity and uncertainty, and for the microfoundations framework of sensing, seizing and particularly transforming.

The second study contributes to the literature on organisation design and provides a research agenda on the blockchain phenomenon by offering insights into how distributed ledger technology (the material) affects the architecture of organisations, resulting in an updated definition of two forms of organisation design: *decentralised* and *autonomous*. Existing organisation design literature views DAOs as organisations where trust is created by experience and forging relationships, decision making is based on expertise and seniority, and governance is established by a board of directors (Ruefli 1971, Dewar and Dutton 1986, Mintzberg 1989, Pacanowsky 1988, Strikwerda 2003). I contribute to organisation design theory by expanding and redefining decentralisation as an organisation design that uses consensus mechanisms and cryptographic primitives to ensure trust among the actors involved (Davidson, De Filippi, and Potts 2016), and by redefining an autonomous organisation as an organisation that is run completely by immutable code, where decision making is automated using smart contract (Swan 2015b, Davidson, De Filippi, and Potts 2016) and governance is embedded in the code (Shrier, Wu, and Pentland 2016).

With the third study I expand the literature on governance in general and agency theory more specifically by including artificial intelligent actors when dealing with unaligned goals and risk preferences among agents and principals. I propose a theoretical framework to help solve the principal–agent problem when dealing with artificial (super) intelligent agents. As such, the third study showed that to minimise the challenges arising from the principal–agent problem when dealing with artificially intelligent agents, organisations should change their governance practices of controlling, monitoring and supervising to include safety measures, such as thoroughly testing the code of AI, analysing the behaviour of the artificial intelligent actor and supervising its learning abilities. Although I studied organisations that developed conversational AI, or chatbots, to understand what organisations can do to contribute to developing responsible AI (the artificial), the learnings are applicable to any organisation developing AI.

Finally, the tripartite approach to sociomateriality, introducing the artificial as an independent actor, assist future research investigations on the impact of artificial intelligence within and on organisations. Conceptualising the artificial as an independent actor within organisations has implications for governance theories such as agency theory, as traditional governance practices involved with human actors no longer apply to artificial actors. It also presents issues for leadership and contingency theories that view organisations as contingent to various internal and external constraints (Donaldson, 2008; Fiedler, 1964; Meyer & Rowan, 1977; Morgan & London, 1998) that will need to accommodate artificial leaders with different objectives, rules and norms than human leaders. Artificial intelligence and agency affect organisational design, structure and strategy and may lead to new strategies and designs, as already occurring with DAOs, where technologies such as big data analytics, blockchain and AI converge. These technologies have implications for strategic management, organisation design and governance practices, amongst many other organisational and management issues. Consequently, the adding of the artificial to the theory of sociomateriality can help scholars better understand how emerging information technologies will influence organisations.

5.5.2 Practical contribution

The contribution for the practice of management lies in the understanding of how the three EITs can contribute in building a new organisation. This information will offer practitioners examples of how big data analytics, blockchain and AI can be used to build an organisation that remains competitive in a constantly changing environment.

Descriptive and predictive analytics can be observed as dynamic strategic capabilities that, when implemented well, can add value to an organisation by providing a better understanding of uncertain and ambiguous competitive environments, and informing strategic decision-making processes. Blockchain is a disruptive technology and managers have to be aware of its possibilities. Incumbents need to investigate how blockchain will affect their organisation and how cryptographic primitives, consensus mechanisms and smart contracts can be applied within the organisation to enable collaboration with industry partners, competitors and customers. Artificial intelligent agents are rapidly becoming more intelligent, and it is a matter of time before AI will surpass human intelligence. To prevent AI from harming those actors involved, organisations should implement governance practices to control, monitor and supervise digital agents. This seems a suitable approach for developers, managers or organisations to solve the principal–agent problem when dealing with AI. Although software will always have bugs, the research shows that problems with such digital agents can be minimised with the right governance practices.

EITs will allow for new types of interactions, moving from pure human-to-human interactions to increasingly human-to-machine and even machine-to-machine interactions, thereby changing existing collaboration practices. This results in social, technological, political and ethical implications that require organisations to adapt their existing processes and become a data-driven organisation. It seems that for many organisations it will be useful to incorporate all three technologies within their organisation, but to understand the impact of such convergence requires further research.

5.6 Limitations and future agenda

While the value of a sociomaterial lens to understand the effect of EITs has been demonstrated, there are also limitation to this approach, which are important to note as they offer insights for future research. Apart from limitations linked to the individual studies, which are discussed in the individual papers, the main limitations of this study relate to datafying analogue processes, understanding the effect of applying all three EITs within one organisation, and verifying the suggestion of adding *the artificial* to the theory on sociomateriality:

First, the literature review results in the suggestion to expand the theory on sociomateriality with a new component, the artificial. Unfortunately, this has not yet been tested and validated empirically. Doing so would have offered great insights into how the artificial would change the philosophical debate surrounding sociomateriality. Although I have shown through the three studies that there is a need for the component of the artificial, I have not been able to verify this using a dedicated study focused on sociomateriality.

Second, the objective of this research was to understand how big data analytics, blockchain and AI can be applied by organisations to remain competitive in an increasingly data-driven future. This has been done through three distinct studies, each focusing on one technology. However, I have not been able to investigate a company that has applied the three technologies within their organisation at the same time. Although there are companies experimenting with the application of the three technologies within their business, accessing them is difficult because of the proprietary knowledge involved, as I observed when approaching a Dutch bank (they were reluctant to cooperate due to the confidential nature of their approach in a competitive market). However, this could likely be part of a longitudinal study to understand how organisations move from a non-data-driven organisation to one applying big data analytics, blockchain and AI, and how that makes an organisation more resilient and competitive in a fast-changing environment. In addition, further research is required to investigate whether these changing interactions between organisations and technologies due to EITs do result in a sustained competitive advantage, especially when all three technologies are applied within one organisation. Such research was outside the scope of this thesis, but would offer important insights if attempted, as well as an opportunity to investigate the tripartite analysis of sociomateriality, which could significantly contribute to the academic discourse on sociomateriality.

Finally, this research focused on three EITs and adding a fourth EIT could have increased the significance of this thesis. However, it would also have increased the scope of the research significantly, beyond that of a doctoral study. Research into the domain of the Internet of Things could have revealed how organisations collect data. As Gurbaxani (2016) notes, for organisations to become a data-driven business, they need to codify their processes; that is, turn analogue processes into digital processes. The Internet of Things covers the domain of datafying analogue processes by connecting devices to the internet, and as such add new data sources that can be analysed for insights (Jesse 2018, Shin 2014, Li et al. 2012, De Mauro, Greco, and

Grimaldi 2015). Various scholars and practitioners have shown it can bring valuable insights to the table (Hashem et al. 2016, Cisco 2014, Jesse 2018). Adding the domain of the Internet of Things could have provided rich understanding of datafication of analogue processes, and how that may affect strategic management or organisation design. Instead, the starting point of my research was any data already present, whether internally or externally. Ignoring the datafication of analogue processes does not negatively affect the results of this research, but incorporating it could have added additional insights for academics and practitioners. Although these three limitations do not negatively affect the results of this study, they do show the need for further research.

EITs and the rapidly changing context are creating a perfect storm for organisations and management scholars studying those organisations. This is because academic research takes time and tends to be backwards-looking, explaining the past on the assumption that the future will be similar, rather than imagining a new future (Roberts and Grabowski 1999). Although this problem does not exist regarding research in the technical aspects of big data analytics, blockchain and AI, it does affect management scholars—by the time a study is published, the reality that was researched might have changed. Nevertheless, there are ample research opportunities for management scholars aiming to explore the combined effect of EITs on strategic management, organisation design and governance. Specifically, contemporary tech startups are investigating new applications of these EITs to disrupt and/or compete with incumbents, thereby helping improve and spread the use of big data analytics, blockchain and AI. Because most of these technologies are very new, only limited research has been done on how the newly developed applications and capabilities will affect organisation design, strategic management, decision making, power and organisational theory.

Within each study included in this research, I have added a research agenda that scholars could focus on to investigate the EITs independently. However, there are also many opportunities for research when these EITs are combined in *the artificial*. Questions that could be investigated are:

- How do artificial actors change strategy and structure, and how can strategy and structure influence the artificial?
- How will the artificial change existing types of organisation design and, potentially, lead to new forms of organisation design?

However, *the artificial* requires a broader research agenda, since big data analytics, blockchain and AI are likely to affect every aspect of human lives, not just business. Hence, questions that researchers could ask could focus on how these EITs affect the social in the broadest sense of the word. Questions could include:

- How does an organisation run by AI operate in society and what are the effects on intuition and experience within an organisation?
- How do non-human and artificial actors differ in their influence on strategic management, organisation design and governance practices?
- How does AI create new technologies and how do these technologies influence humans, organisations and societies?

In addition, artificial artefacts are editable, open and distributed, and they possess infinite expansibility (Nambisan 2017), resulting in even more questions that could be investigated by future scholars, including:

- What does the artificial mean for existing organisation theory?

- How will the artificial require researchers to rethink existing organisation and social theories?

Many questions remain and in coming years the artificial offers substantial new areas of research for future scholars, potentially updating a vast number of existing management theories by incorporating the artificial.

Chapter 6: Conclusion

EITs change how we organise activities within organisations. The theory of sociomateriality helps to understand the social and material when dealing with these technologies within organisations. Although matter has mattered since the entanglement of the social and the material, resulting in an ethical dimension that shapes future ways of conceiving and enacting sociomaterial arrangements (Carlile et al. 2013, Scott and Orlikowski 2012), it has also resulted in a debate around what the material is and whether or not the social and the material are actually entangled. The social and material agencies imbricate within a technical subsystem but when talking about EIT systems, things become more difficult, as material and artificial elements increase the complexity of the system and 'how IT enacts new actors, opens up new possibilities and creates realities that were not previously perceived' (Leonardi 2012, 11); hence the need for the artificial. Yet, artificial intelligent agents are a new and prominent actor within organisations, and not yet fully understood. How objects, artefacts and materiality matter within organisations is increasingly important in organisation studies, especially when dealing with the artificial. As such, I argue for a tripartite analysis of EITs, consisting of the social, the material and the artificial. Within this tripartite analysis of sociomateriality, the notion of performativity remains helps understanding organisation design in times of artificial actors. These artificial actors are created within a certain framework and based on certain mathematical models that, when becoming part of the organisation, will then affect that organisation and how influence stakeholder's interactions. As such, the objective is that a tripartite analysis of sociomateriality will help scholars, as well as practitioners, understand how humans, technology and artificial intelligence are interrelated with each other and how they will influence each other in action. Adding the artificial to the theory on sociomateriality and seeing it as an independent actor within an organisation helps shed light on how the three EITs affect organisations, how they will change organisation design, and what the impact will be on strategic management and governance. It can help scholars better understand how the artificial will influence organisations and is likely to result in a variety of existing theories needing to be updated, in addition to changes to the dynamic capabilities theory, organisation design and agency theory, as discussed in the three studies of this thesis. Not only scholars will benefit from including the artificial in their research. It will also enable practitioners to better understand the effect of these technologies—especially important in today's digitalised environment; that is, 'the encoding of analogue information into digital format', differs from earlier technologies (Yoo 2010, 725) and the more sophisticated the technologies that are adopted, the more profound the effect on organisations (Huber 1990a). The findings of the three studies confirm this. Descriptive data analytics improves the capability of an organisation to understand the business context and predictive data analytics helps in the realisation of business opportunities. Therefore, big data analytics can be seen as a dynamic organisational capability that supports strategic decision-making in times of ambiguity and uncertainty. Blockchain removes the need for trusted intermediaries and enables immutable transactions and decisions to be executed automatically and autonomously, resulting in two new types of organisation design, to be included in the discourse on organisation design, that use cryptography to ensure trust, apply smart contracts to automate decision-making and embed governance into the code. Finally, artificial intelligence will require different governance practices if organisations want to solve the principal-agent problem when dealing with artificial agents, thereby expanding agency theory when artificial intelligence is involved.

In addition, I wanted to show practitioners[xii] how big data analytics potentially empowers consumers and employees, resulting in open strategy and better understanding of the ambiguous and uncertain environment; how blockchain enables peer-to-peer collaboration with industry partners and/or customers and enables trustless transactions governed by cryptography and smart contracts; and how AI allows for new and different levels of intensity and involvement among human and artificial actors, and the measures organisations can take to develop responsible AI. With that, new modes of organising are emerging, where technology facilitates collaboration between stakeholders and where human-to-human interactions are increasingly replaced with human-to-machine and even machine-to-machine types of interactions. This requires practitioners changing how they organise activities within and across organisations. These characteristics call for increased flexibility and creativity in organisations (Yoo 2013) and a 'continuously developing absorptive capacity to improve the overall innovation capability' (Assink 2006, 227). With a great deal of incumbent organisations still making strategic choices based on experience and intuition (Khatri and Ng 2000, PWC 2015), many are facing significant challenges and radical change when developing such innovation capabilities. However, organisations have to adapt to the constantly changing environment if they want to avoid a 'Kodak moment'.

[xii] This research will be published as a management book with Routledge. The title will be: *The organisation of tomorrow: How AI, blockchain and analytics turn every organisation into a data organisation*— Publishing contract with Routledge attained, contract signed and book to be published in Q1 2019.

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