Assessing the Impact of Automation on Decision Making within Large Organisations

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Declaration

I declare that this thesis, Assessing the Impact of Automation on Decision Making within Large Organisations' is my own work. No part of this thesis has been published previously. This thesis has been prepared for submission to the University of Warwick Business School as consideration for the award of Doctor in Business Administration. I confirm that no part of this thesis has been submitted for a degree, or otherwise, to any other university. When reference is made to the work of others, the extent to which it has been used is indicated in the text and bibliography. Any errors or omissions within this thesis are the sole responsibility of the author.

This document contains 82,780 words (excluding images) and therefor conforms to the indicative word count stipulated by Warwick Business School.

Abstract

We can summarise much of what is known about organisational decision making as follows. Human unaided decision making is frail and subject to error. Economically rational organisations seek to maximise utility for owners and protect themselves from the self-serving behaviours of their stewards. Organisations have sought to deploy decision aids since the 1980s with mixed success. Recent advances in automation support decision making across a range of contexts, processing information with a tireless impartiality. Technology deployment is a dialectic of accommodation and resistance between material and human agency.

Predicated on the foregoing, the question to be answered is simply this: given recent advances in automation where and to what extent should leaders consider deploying machines to support decision making in large organisations?

We conduct a narrative literature review before using an abductive framework to perform qualitative fieldwork - interviewing 25 senior leaders from large organisations. The resultant transcripts provide unique insight into the knowledge, attitude, and practice of such leaders.

We highlight that data fuels the automation of decision making, that human judgement and experience will continue to be valued in relation to high-stakes decisions, and finally, that accommodation and resistance will increasingly be subject to factors external to organisations.

We use our findings to build a dynamic model for practice centred around three decision zones.

Our work makes a theoretical contribution by reframing multi-disciplinary discourse considering recent advances in automation. We make a methodological contribution by answering Bailey & Barley's (2020) call to gain insight into the interests and agendas of those responsible for automation decisions. Finally, we make a practical contribution by supporting leaders to determine where to deploy automated decision-making solutions to greatest effect. We refine our model through feedback from two of the world's leading advisory firms.

Abbreviations

AI	Artificial Intelligence
DNN	Deep Neural Networks
EQ	Emotional Quotient or Emotional Intelligence
GDPR	General Data Protection Regulation
HR	Human Resources
IQ	Intelligent Quotient
KAP	Knowledge, Attitudes and Practices
ML	Machine Learning

Chapter 1: Introduction

1.1 Background

Rapid advances in automation technology, including artificial intelligence, have seen machines encroach into areas historically considered the exclusive domain of human agents. In recent years machines have moved beyond the abstract feats of beating the best players in the world at chess, Go and Jeopardy to increasingly displace human workers across a range of industries. The so-called fourth industrial revolution (Schwab, 2015) has heralded a new paradigm of automation where routine, repetitive cognitive, and manual tasks are increasingly performed by machines (Autor *et al.*, 2003b; Frey & Osborne, 2017; Kolbert, 2016; Lee, 2018). From cooking burgers at fast food restaurants to automating a myriad of warehouse activities - machines are performing ever more complex tasks and the trend is accelerating exponentially.

In recent years autonomous vehicles have moved from the realms of science fiction and are expected to underpin a $7 trillion market by 2050 (Gill, 2020). As such we are rapidly approaching the point where machines will make life and death decisions about collision scenarios on our roads (Awad *et al.*, 2018; Bigman & Gray, 2018; Bigman *et al.*, 2019). In parallel, self-guided weapons have the potential to transform the nature of global warfare – making decisions that would previously have been in the hands of highly trained military personnel (Horowitz, 2016). In medicine, machines are increasingly prevalent in diagnosis, interpreting data in a manner that few, if any, human experts are capable of matching (Jha & Topol, 2016). As such, decisions across a range of disciplines will increasingly be made by, or augmented by, machines - colliding ethical and moral decision making in a way that philosophers have debated in the abstract for centuries.

Despite the foregoing, the impact of automation on organisational decision making is currently underserved in the literature. We seek to redress this balance, acknowledging that 'automation does not occur at the job level but rather at the task level' (Sampson, 2020, P.122) and that 'the task of "deciding" pervades the entire administrative organisation' (Simon, 1945 , P.1) As such we might think of organisations as decision making systems. Given the trends we are seeing in transportation, the military and medicine we might reasonably expect automation to materially disrupt the way that such organisational decisions are made. As Berente et al note 'the interaction between human and autonomous AI is perhaps the key managerial issue of our time' (Berente *et al.*, 2021, P.1440).

The literature on human decision making is vast and explored from a variety of academic perspectives from psychology through to business management. Organisations in turn have been much studied, with the theory of the firm generating significant discourse since the 1930s. Machines and automation are highly topical, and we have seen an exponential increase in associated literature in recent years. Yet despite the academic coverage of each of these distinct areas we find that the impact of automation on decision making within organisations is somewhat lacking. We are seemingly not alone in this observation, as evidenced by a recent special edition of MIS Quarterly (September, 2021) dedicated to managing AI, within which all eight articles highlight the role of automation on decision making.

1.2 Research Question

We are motivated by a simple, but unanswered question: given recent advances in automation, where and to what extent should leaders consider deploying machines to support decision making in large organisations?

1.3 Extant Literature Summary

As we have highlighted, the literature on this topic is broad and growing. Entirely new disciplines have emerged in recent years regarding machine decision making and most proximally machine ethics and morality. Our research calls for a multi-disciplinary approach since exploration of any one of these areas in isolation is unlikely to provide the rounded insight required to answer the question posed (Bailey & Barley, 2020; Berente *et al.*, 2021).

Within this paper we begin by exploring the existing literature via a narrative review. We consider unaided human decision making – exploring inter alia, heuristics, intuition, and regret. We find that human decision making materially departs in many instances from the axioms of economic theory (Stanovich & West, 2000). Human agents are cognitively bounded, resulting in decisions that 'satisfice rather than maximise' (Simon, 1945, P.118). The inability to adequately distinguish between instinctive system one and more rational system two methods can lead to 'severe and systematic errors' (Kahneman, 2003, P.1452). Yet these tools equip unaided human decision makers to deal with complexity in a world where 'acting fast can be as important as being correct' (Gigerenzer & Goldstein, 1996, P.660). We find the literature does much to explain both the methods and associated limitations of unaided human decision making. We find the literature does much to explain both the methods and associated limitations of unaided human decision making. What the literature does not tell us is where and to what extent such decision making should be deployed were more rational alternatives to become available.

We go on to explore organisational decision making. Agency theory has long dominated management discourse. In short, as organisations grow in complexity, tensions arise between equity owners and the individuals employed to manage the organisation on their behalf. As decisions become increasingly removed from owners, information asymmetry increases, and it can become increasingly difficult to ensure that self-serving stewards make decisions that maximise the principal's rather than their own utility Cyert *et al.*, 1956; Cyert, 1963; Eisenhardt, 1989; Hendry, 2005; Jensen & Meckling, 1976). A raft of mechanisms have been established over the years to redress this balance – including the establishment of independent boards of directors (Fama, 1980; Fama & Jensen, 1983). However, this conflict has never been fully resolved. Nor have organisations ever overcome the inherent frailties and limitations of their human decision makers. Organisations collectively are forced to make compromised decisions – leading to organisations that are as bounded as their employees (Cyert *et al.*, 1956; Cyert, 1963; Dew *et al.*, 2008). We are left somewhat frustrated by the literature in terms of where human decision-making ought best be deployed within organisations. If organisations ultimately exist to maximise the returns for their various stakeholders – would they not be best served by maximising utility rather than making decisions which are merely 'good enough' (Van Ees *et al.*, 2009, P.312). Again, in a scenario where alternatives to human decision making were to become available - where might such methods be deployed to best effect and why?

Our review of the literature concerning machine decision making highlights that 'the computer revolution has blurred the line between physical and mental tasks' (Agrawal *et al.*, 2018, P.2). Machines arguably do not suffer from the frailties associated with unaided human decision-making - processing data in a rational, impartial, and tireless manner. We highlight that machines have historically struggled to overcome Dreyfus's (1972) epistemological challenges and the frame problem (McCarthy & Haynes, 1969). We suggest however that in recent years the number of connected devices and the increasingly digital nature of modern organisations may have started to redress this challenge. We highlight the role of machine learning and reflect on the role of trust and black-box techniques. Despite significant literature concerning driverless vehicles, autonomous weapons, and application of machine learning within the medical sector – we are left unsatisfied with the literature's coverage of our basic research question. Given that inorganic alternatives to human decision making are increasingly available and are improving at pace - where and to what extent should such automation be deployed?

We go on to explore this question within an organisational context – reviewing literature on aided decision making within organisations. We highlight that such discussion is not new – with a rich literature existing from the 1980s from simple fault trees (Fischhoff *et al.*, 1978) to more sophisticated tools. We note Edwards et al's (1992) assertion that organisational decisions exist across three levels – namely operational, tactical, and strategic. We acknowledge both Edwards et al (1992) and Cyert et al (1956) assertions that machines are best suited to operational and tactical decision making – struggling with the unstructured nature of strategic choices. Yet we are again left somewhat dissatisfied. Given the frailties of human decision making, the long-debated challenges of the impact of such frailty on organisational decision making and the presence of seemingly viable alternatives – where and to what extent should human and machine decision making be deployed?

Finally, we bring the disparate parts of our literature review together by considering Pickering's (1993) mangle of practice. The mangle allows us to neatly consider the relationship between machines, human agents, and organisational contexts. The resultant dialectic is a useful way to frame the debate, considering the question – does technology shape organisations or do human agents shape technology (Rose & Jones, 2005)? We are left to consider whether the nature of Pickering's accommodation and resistance, and even the nature of material agency itself, has been impacted by recent advances in automation.

1.4 Open Questions

We find that the broad literature reviewed provides insight into our core question – but does not address it to our satisfaction. We might summarise what is known as follows. Human decision making is frail and subject to error. Economically rational organisations seek to maximise utility for their owners and protect them from the self-seeking behaviours of their stewards. Organisations have sought to deploy automated decision making since the 1980s with mixed success. Machine decision making increasingly supports automated decision making across a range of contexts, processing information with a tireless impartiality. Finally, technology deployment is a dialectic of accommodation and resistance between material and human agency. Yet the foregoing fails to provide adequate guidance to leaders regarding where and to what extent machines should be deployed to support decision making in large organisations.

1.5 Our Methods

In keeping with Bailey & Barley we recognise that 'behind the design and adoption of technologies lie interests and agendas' (Bailey & Barley, 2020, P.2). This point is complemented by Lebovitz et al (2021) who suggest that it is critical that we 'understand how managers evaluate AI tools as such evaluations drive their adoption' (Lebovitz *et al.*, 2021, P.1502). As such we believe that the knowledge, attitudes and practices of senior leaders who 'create, purchase, and use intelligent technologies' (Bailey & Barley, 2020, P.10) will materially shape the future scope and pace of technology adoption within organisations. We deploy abductive reasoning and qualitative methods to unpick the foregoing and address our research question.

Using Rubin & Rubin's (2012) responsive interviewing methodology we speak with 25 senior leaders, resulting in over 170,000 words of transcript. Our discussions cover C-suite leaders, service providers, advisory firms, and board members. The foregoing addressing Bailey & Barley's call for a unified approach that considers 'power dynamics beyond the organisation as well as those that shape the processes of design, adoption and implementation' (Bailey & Barley, 2020, P.7). The resultant insight and discussion is unique within academia.

We are guided by Gioia et al (2012) in analysing our work – using NVivo to code our transcripts. We identify 31 level one codes, 10 second order themes and three aggregate dimensions. In terms of the latter, we identify that data fuels automated decision making, that human judgement and experience will continue to be valued by organisations in relation to high-stakes decision making. Finally, we suggest that Pickering's mangle of practice is increasingly impacted by a dialectic external to the organisation.

1.6 Our Model

Based on our research findings we propose a model that assists academics and practitioners to answer the dynamic and evolving question posed at the outset. Our model identifies three decision zones highlighting the characteristics, appropriate automation strategy and considerations associated with each. Our model also includes accelerators – highlighting that machines will continue to encroach into what we have affectionately labelled grey-zone decision making. By contrast we highlight that customer, professional body and regulatory resistance will likely result in a dialectic of accommodation and resistance that will potentially impact our identified engineering bottlenecks. The inclusion of accelerators and inhibitors reflects a dynamic and evolving environment (Berente *et al.*, 2021). Our model can be used by practitioners as a diagnostic tool to assess where to deploy automation to greatest effect. We provide a worked example for completeness. Our model has been reviewed by two of the world's leading advisory firms and refined based on feedback.

1.7 Our Contribution

Our work makes material theoretical, methodological, and practical contributions.

1.7.1 Methodological

We answer Bailey & Barley's call for scholars to research the 'interests, goals, and perspectives of those who had the authority to authorize the purchase' (Bailey & Barley, 2020). In contrast to traditional approaches of using quantitative methods and databases to explore the impact of automation as exemplified by various works by Autor and contributors – we deploy qualitative methods. The access granted to senior leaders including C-suite and the board provide unique insight. Our approach provides depth and insight into the knowledge, attitudes and practices of a powerful stakeholder group who will be critical in shaping the future of automation within their respective organisations.

1.7.2 Theoretical

Our work is grounded in a narrative literature review, contributing to an increasingly 'boundary spanning, interdisciplinary' (Berente *et al.*, 2021, P.1434) discourse. We highlight that questions related to the automation of organisational decision making are far from new. That said, recent advances in technology have changed our practical ability to answer them. As such we revisit classic literature and reframe it in light of recent developments. Our contribution to the debate on expert systems, reframing of Dreyfus's (1972) epistemological defence taking into account the advancement of connected devices and machine learning, and extension of Pickering's (1993) mangle of practice are of particular importance.

1.7.3 Practical

Our work culminates in a model for practice. We reduce our research findings to a simple and easy to use model that practitioners can apply to help answer the question posed. Without such practical guidance 'firms lacking an understanding of the benefits and limitations of AI could misallocate valuable AI resources to the types of projects where AI provides minimal benefits' (Jingyu *et al.*, 2021, P.1452). Few models can provide definitive answers and ours is no exception – however it provides a useful and dynamic model that can be applied as a diagnostic tool to help organisations to develop their automation strategy. The model acknowledges an 'ever-evolving frontier of computational advancement' (Berente *et al.*, 2021, P.1433) helping organisations to evolve their thinking over time predicated on identified accelerators and a dialectic of accommodation and resistance that will increasingly be external to the organisation.

1.8 Why This Research Matters

The world is being fundamentally disrupted by technology and the trend is set to accelerate. Almost every aspect of our day-to-day life is being impacted by imperceptible advances in automation that have become so commonplace and ubiquitous that they 'disappear into the background to the extent that we forget their very existence' (Newman *et al.*, 2019, P.10). Domains classically associated with human agency are increasingly challenged as automation addresses 'ever more complex decision-making problems' (Berente *et al.*, 2021, P.1433). Decision making within large organisations will not be exempt from such disruption.

All else being equal technology will materially disrupt organisational decision making. For those ahead of the curve it will become a competitive advantage. For those that fail to adapt quickly enough it will likely become an existential crisis. It would appear that there is room for both machines and humans in that organisational future. However, understanding where to deploy automated and human agents to greatest effect is critical if one is to avoid pilot paralysis, overcome resistance (both internally and externally) and achieve exponential business outcomes. The question we pose herein cannot be ignored, yet it is not yet receiving the attention it merits. The following discourse represents our modest attempt to redress this balance.

1.9 Structure

We begin our paper with a narrative, scoping review of the existing literature. We identify a number of open questions based on perceived anomalies which we use to inform our methods. These methods are set out in detail. We follow this by providing a summary of our results against three aggregate dimensions. From here we move on to discuss our results in light of the previously reviewed literature. Based on this discussion we propose a model for both academics and practitioners to support the dynamic question behind our research – highlighting the implications for practice. We test our model with two of the world's leading advisory firms using feedback to refine and enhance the same before providing a worked example. We acknowledge the limitations of our work and provide suggestions for further research. Finally, we set out our contribution and offer concluding comments.

Chapter 2: Literature Review

2.1 Literature Review – Our Approach

Jesson et al remind us that the first step in any research project is to assess what is already known – suggesting that 'to produce 'good literature reviews' does not come naturally' (Jesson, 2011, P.3). Our area of interest is broad given that we seek to cover 'cross-disciplinary' (Hart, 2018, P.13) themes across broad literature sets covering inter alia, individual human decision making, organisational decision making and machine decision making. In so doing we cover themes across business management, automation theory, economics, philosophy, and behavioural psychology. Thus, we acknowledge Berente et al's guidance that to appropriately study the impact of technology we must follow a 'boundary-spanning, interdisciplinary tradition' (Berente *et al.*, 2021, P.1434). We equally acknowledge the challenge posed by Jesson (2011) that many authors fail to explain the theoretical approach underpinning their literature review confusing critical, systematic, and narrative approaches amongst others. Given the nature of our research area and the breadth of material we seek to review – we have undertaken a 'scoping' literature review:

> "The review documents what is already known, and then, using a critical analysis of the gaps in knowledge, it helps to refine the research questions, concepts and theories to point the way in future research" (Jesson, 2011, P.15).

The sheer breadth of our ambition makes it ill-suited to a fully systematic literature review at this stage and we acknowledge that such reviews may subsequently follow as part of future work.

Notwithstanding the foregoing, we acknowledge that the literature on automation and particularly artificial intelligence and machine learning is growing rapidly. As with any study in a rapidly evolving discipline there is always a danger that new material emerges that could have an impact on one's work. Given the plethora of recent articles and the sheer breadth of our subject matter that challenge is acute. Although the core of our literature review was conducted in 2019, to address this challenge we pay close attention to the special edition of MIS Quarterly issued in September 2021 which focuses expressly on managing artificial intelligence. The eight papers reviewed provide good insight into recent thinking and help provide assurance that the topics covered in this paper remain relevant and take account of recent developments.

Having addressed one potential challenge, we acknowledge two further criticisms of narrative literature reviews. The first is the lack of obligation to 'provide a method report' (Jesson, 2011, P.25). In other words, such reviews typically do not set out the basis on which materials have been identified and deemed worthy of inclusion which would make them both 'explicit and reproducible' (Fink, 2014, P.6). The second is that such a review can create a 'bias sample of the full range of literature' (Torgerson, 2003, P.5).

On the former concern, we have sought to be even handed in our identification of materials – using key word searches in academic databases[1] to identify peer reviewed journals and prioritising those that have received the greatest number of citations. We have set out search words, together with our review methodology in Appendix I. Our review has been corroborated through discussion with supervisors and consideration of sources cited within core texts. As such we hope to overcome the objection of Fink that 'subjective reviewers choose articles without justifying their search strategy, and they give equal credence to good and poor studies' (Fink, 2014, P.6). Regarding the second objection, we have sought to not be either overly critical or embracive of materials in our literature review – reporting what has been captured rather than expressing an independent view as to efficacy. The purpose of our scoping review is not to overly critique the positions set out in the papers reviewed – but rather to identify potential anomalies between our lived experience and the extant literature. We return post our subsequent research to offer our perspective – but choose not to do so ahead of time. As such our narrative literature review provides a balanced and representative view of the theory that exists today.

Our literature review explores the existing theoretical landscape concerning decision making. We begin by exploring theories underpinning, unaided, individual human decision-making – considering utility theory, bounded rationality, heuristics, intuition, regret, and bias. We then move on to consider organisational decision making considering the rational theory of the firm, agency theory, standard operating procedures, and the role of the board. We acknowledge that both individuals and organisations will often make decisions which are satisficing rather than optimal. From there we consider the nature of machine decision making before reviewing the impact of the same on organisations. Finally, we consider how accommodation, resistance and both human and material agency are likely to impact the breadth and scale of adoption.

[1] We have predominantly used SCOPUS as an academic database.

2.2 Some Definitions

2.2.1 Decision Making

Decision making is a term that has 'broad meaning', (Agrawal et al, 2018, P.3) and as such, definitions are required to ensure clarity. We borrow our definitions from the work of Agrawal et al (2018) who define decision making as the process of arriving at an action in the face of choice or uncertainty, or, 'the mental processing that leads to the selection of one among several actions' (Newell & Shanks, 2014, P.2). Any such decision involves assessing the value associated with likely outcomes, with these anticipated outcomes being referred to as 'payoffs' (Agrawal et al, 2018 and Bolton & Faure-Grimaud, 2009). The process of arriving at payoffs – is often referred to as *judgement*. As Evan's neatly summarises:

> "The theory of rational decision making, which was imported into psychology from the discipline of economics, requires that a rational person should anticipate the consequences of their decisions, estimating the probability and utility of various outcomes, combining the two to calculate the expected utility of each action, and then choosing the action that maximises this quantity" (Evans, 2010, P.320).

At its' heart the process of decision making is fundamentally about 'evaluating consequences' (Jha & Topol, 2016, P.27) or perhaps more specifically assessing *likely* consequences - given that one can only evaluate the relative merits of a particular decision with posteriori knowledge.

2.2.2 Tasks and Skills

As Sampson (2020) highlights, early studies exploring the impact of automation focused on job and industry. However, 'while a job taken as a whole may not be susceptible to being automated, individual tasks within the job may be easily automated' (Sampson, 2020, P.123). Acemoglu and Autor explore both task and skills - defining the former as 'a unit of work activity that produces output' (Acemoglu & Autor, 2011, P.1118). By contrast a skill can be considered 'as a worker's endowment of capabilities for performing various tasks' (Acemoglu & Autor, 2011, P.1118). Skills are applied to tasks to create output. Decision making may be considered as a *task* that pervades organisations – whilst *effective* human decision making may be considered a *skill*.

2.2.3 Hard and Soft Skills

Commentators and practitioners alike commonly differentiate between hard and soft skills – with the former defined as the 'understanding of, or proficiency in, specific activities that require the use of specialized tools, methods, processes, procedures, techniques or knowledge' (Katz, 1974, P.1299). These hard, cognitive skills – which are readily learned and considered a mainstay in most educational pedagogy are characterised by well-defined explicit knowledge in fields such as medicine – contrast with their softer, less tangible counterparts. The latter is defined as 'personality traits, goals, motivations and preferences' (Heckman & Kautz, 2012, P.451) – with commentators tending to highlight soft skills in terms of traits as opposed to particular competencies. If decision making can consider a task – we question the extent to which effective human decision making may be considered a hard or soft skill.

2.2.4 Technology Nomenclature

Within the literature we find a range of nomenclature used when describing technology. We find that artificial intelligence (Bailey & Barley, 2020; Berente *et al.*, 2021; Charlwood & Guenole, 2022; Fügener *et al.*, 2021; Huang & Rust, 2018b; Jingyu *et al.*, 2021; Lebovitz *et al.*, 2021; Lou *et al.*, 2021), automation (Acemoglu & Autor, 2011; Brynjolfsson *et al.*, 2018; Sampson, 2020), computerization (Autor *et al.*, 2003b; Sampson, 2020) intelligent technologies (Bailey & Barley, 2020) and machine learning (Brynjolfsson *et al.*, 2018; Sturm *et al.*, 2021; Teodorescu *et al.*, 2021; van den Broek *et al.*, 2021) amongst others, are used interchangeably and often without definition. Borrowing from the office of AI, Charlwood & Guenole usefully define two critical terms – namely, artificial intelligence and machine learning as follows:

> "AI is typically defined as the use of digital technology to create systems capable of autonomously performing tasks commonly thought to require human intelligence. In contrast to popular representations of artificial intelligence in science fiction, recent advances in AI have occurred in the field of machine learning (ML), a sub-set of AI where digital systems autonomously improve their performance at undertaking a specific task or tasks over-time as the system learns through experience" (Charlwood & Guenole, 2022, P.3).

Consistent with this definition Brynjolfsson et al suggest that artificial intelligence is a general-purpose technology – 'that becomes pervasive, improves over time, and generates complementary innovation' (Bressnahan & Trajtenberg, 1995 as quoted in Brynjolfsson et al

(2018). Expanding on the point regarding complementary innovation we find a 'suite of associated technologies that complement or contribute to it [artificial intelligence], such as machine learning, big data, robotics, smart sensors, the internet of things, and analytics' (Bailey & Barley, 2020, P.1). Finally, Berente et al offer a definition of AI which perhaps most adequately represents our perspective, stating 'AI is not a technology or set of technologies, but a continually evolving frontier of emerging computing capabilities' (Berente *et al.*, 2021, P.1433).

It is not our intention within this paper to define the full scope of the phrases referenced above and covered by the literature. The exercise would be a mammoth undertaking and potentially yield limited explanatory power. It is important however for us to set out our own use of language. Our predominant concern is with automation at the aggregate level. We devote limited time to exploring the intricacies of specific technology. Instead, we focus on the ability for technology in its various guises to substitute for human labour – regardless of method. We acknowledge that technology is 'manifested by machines' (Huang & Rust, 2018a) which we take to refer to a combination of hardware and software. Within this paper we refer to automation, technology, and machines interchangeably. Where we wish to refer to a particular technology, technique, or form of automation we call it out specifically in the associated text.

2.3 Part 1: Unaided Individual Human Decision Making

Decision making is fundamental to everyday life and 'one of the most important recurrent human activities' (Hogarth, 1989, P.ix). Many decisions are made on a subconscious level, so quickly and intuitively that they barely register as decisions. In any decision-making process there are consequences reflected in the differentiated outcomes based on choice. In attempting to make good rational choices, decision makers seek to maximise value, reflecting the common-sense maxim that choices should be made based 'on the prediction of how likely the good rather than the bad state will arise' (Agrawal *et al.*, 2019, P.2). Human history is littered with examples of celebrated personalities who have made critical decisions that have resulted in differentiated outcomes altering the course of history - from Napoleon's ill-fated invasion of Russia in 1812, through to Stanislav Petrov who averted a nuclear war by ignoring the advice of his console in 1983. On a less grandiose scale, good judgement is highly prized in almost all human professions and serves to differentiate elite workers.

Von Neumann and Morgenstein's utility theory suggests that a rational agent should 'anticipate the consequences of their decisions, estimating the probability and utility of various outcomes, combining the two to calculate the expected utility of each action' (Evans, 2010, P.320). However, this is not typical of the 'way real people think' (Todd & Gigerenzer, 2001, P.729) given human cognitive limitations and the scarcity of time. Economic theory views 'the mind as a Lapcaen Demon, equipped with unlimited time, knowledge, and computational might' (Gigerenzer & Goldstein, 1996, P.650). However, the reality is that most agents, unaided by decision support tools, find themselves in real world situations facing imperfect information, a narrow window in which to make a decision and constrained cognitive abilities with which to assess options. Simon thus suggests that rationality is bounded by the complexity of the world we live in relative to our cognitive abilities. This in turn leads 'bounded human' agents to make decisions that 'satisfice because they have not the wits to maximize' (Simon, 1945, P.118). In other words, the combination of real-world complexity and cognitive limitations results in unaided decisions that are more satisfactory than optimal.

Given that human decision makers in the majority of instances are incapable of 'flawless and costless deduction' (Sandholm and Lesser, 1997, P.100) humans have evolved effective coping mechanisms that enable decisions to be made in complex environments. In such instances, the quality of a decision must be weighed up against the cost associated with computation. This has given rise to the notion of heuristics[2]:

> "Heuristics are efficient cognitive processes, conscious or unconscious, that ignore part of the information. Because using heuristics saves effort, the classical view has been that heuristic decisions imply greater errors than do "rational" decisions as defined by logic or statistical models" (Gigerenzer & Gaissmaier, 2011, P.451).

Todd and Gigerenzer invite us to consider the human decision maker as 'a bounded mind reaching into an adaptive toolbox filled with fast and frugal heuristics' (Todd & Gigerenzer, 2001, P.729). Human agents have thus adapted to respond to complex environments by quickly and efficiently focusing on what they perceive as relevant information whilst happily discounting that which they consider superfluous.

That said, complexity and limited cognitive capacity are not sufficient to explain unaided, individual decision makers departure from rational theory. As we have seen, utility theory assumes that agents will make decisions on the basis of those choices that are most likely to

[2] We acknowledge that heuristics have been used as an AI technique. In this section our concern is within unaided human decision making – we review automation and decision support in subsequent sections.

lead to outcomes which increase utility. The model is considered by advocates to be so compelling that any ‘situations in which decision makers violate the axioms consistently are referred to as ‘paradoxes’’ (Bell, 1982, P.96). However, in practice human decision makers often demonstrate ‘systematic irrationalities’ (Stanovich & West, 2000, P.645) when contrasted to such theory. Allais Paradox is a celebrated example highlighting the inconsistency with which human decisions are made. Whilst as we have seen, we can, on occasion, attribute such paradoxical behaviour to cognitive limitations this is insufficient to explain away all such discrepancies.

Loomes and Sugden (1982) and Bell (1982) independently developed theories that moved beyond the pure economic perspective of ‘decision making as a cold cognitive process’ (Zeelenberg, 1999b, P.325) to take account of regret. The theory posits that human decision makers experience regret in response to decisions made and that such regret impacts choices in a number of material ways ignored by utility theory. Regret can be defined as ‘the painful sensation of recognising that ‘what is’ compares unfavourably with ‘what might have been’ (Sugden, 1985, P.77). Zeelenberg (1999b) highlights a number of instances where regret is likely to be experienced. Regret is most typically associated with complex decisions which are close in utility, where probabilities are difficult to assess or where one is forced to trade off two important attributes (Sugden, 1985).

Whilst regret is experienced after a decision is made, the key tenant of regret theory suggests that its *anticipation* can have a material impact at the point of choice:

> “Thus, people are motivated to avoid post-decisional regret. This regret aversion has a profound influence on their decisions, because the possibility of regret is anticipated, and subsequently taken into account when making decisions” (Zeelenberg, 1999a, P.101).

The anticipation of regret can result in decision makers making both risk averse and risk seeking choices and is highly dependent on the situational context (Larrick & Boles, 1995). However, whilst one’s approach to risk will depend on context and appetite, the ‘minimax regret principle’[3] (Zeelenberg, 1999b) suggests that agents anticipate the amount of regret likely to be experienced and often choose the option where regret is likely to be minimised.

[3] We note that certain AI techniques adopt a similar approach to train software.

Given that rational decision-making theory takes no account of regret in making effective choices – should we consider it to be an irrational variable? Sugden (1985) responds to such suggestion by arguing that regret is a cognitive emotion and its *existence* should not itself be debated as matter of rationality. Regret is an experienced event over which a decision maker can have no control and as such Zeelenberg highlights that the 'rationality question should focus on whether it is rational to act on our emotions, and not the emotions themselves' (Zeelenberg, 1999b, P.328). Regret enables us to learn from our experiences (Hogarth, 1989; Larrick & Boles, 1995; Sugden, 1985; Zeelenberg, 1999a; Zeelenberg *et al.*, 1996), to course correct actions that have proved erroneous and encourage agents to take more considered approaches in future decision making.

If regret is uniquely organic and a material factor in individual, unaided, decision making - then so too is intuition. We have previously commented on the role and nature of heuristics. These simple processes enable humans to deal with complexity with minimal computational effort. However, it is important to distinguish between heuristics and intuition. Intuition can be considered as the 'immediate apprehension in the absence of reasoning' (Evans, 2010, P.313) and contrasts with the slower, reflective processes associated with rational thought. Evans argues that the majority of human decisions are made on the basis of intuition - suggesting that such methods enable 'large amounts of information processing' (Evans, 2010, P.313). Far then from the notion of rational decision-making, intuitive choice is made without active cognitive reasoning or explicit understanding of the process underpinning it. These mental states come easily to mind being highly accessible – 'monitoring is normally lax and allows many intuitive judgements to be expressed, including some that are erroneous' (Kahneman, 2003, P.1450). Thus, whilst intuition may be an efficient coping mechanism – the strong feelings of confidence that arise – can lead to 'severe and systematic errors' (Kahneman, 2003, P.1452). These errors occur as result of bias – both conscious and unconscious leading many to observe that 'human judgment is itself deeply flawed' (Agrawal *et al.*, 2019, P.6):

> "To what extent do we know our own minds when making decisions? Variants of this question have preoccupied researchers in a wide range of domains, from mainstream experimental psychology (cognition, perception, social behaviour) to cognitive neuroscience and behavioural economics" (Newell & Shanks, 2014, P.1).

Given the prevalence of intuition and emotions such as regret in unaided human decision making it is perhaps unsurprising that Morewedge et al (2015) suggest that bias is prevalent across policy, law, medicine, education, business and individual's private life's affecting both novices and highly skilled professionals alike.

As we have seen agents use a combination of heuristics principles and intuition to reduce complex tasks to simple principles, which in general are highly effective - but that can 'lead to severe and systematic errors' (Tversky & Kahneman, 1974, P.1124). Errors of representativeness, base rate frequency and misconceptions of regression are all examples of common unconscious bias. Whilst reasoning can be deployed to override intuition and reduce bias – such reflections are often applied after an event 'confabulating justification for our intuitions and constructing the illusion of conscious control' (Evans, 2010, P.323). In other words, reasoning is often used subconsciously to justify intuitive decisions after the event rather than challenge in the moment. Feedback is critical to being able to correct poor decisions and to learn from errors in judgement enabling agents to make better informed decisions in the future. However, regret and bias also play a role in the extent to which decision makers actively seek such feedback:

> "When the outcomes of a foregone alternative is learned, it constrains counterfactual reasoning to the outcomes that actually occurred… Thus, a decision maker has leeway to rationalise a decision by assuming that the foregone alternative would have yielded a worse outcome" (Larrick & Boles, 1995, P.95).

Thus, decision makers may choose to avoid gaining feedback that results in regret or other negative emotions and consciously or otherwise reframe situations to rationalise erroneous decisions made (Tversky & Kahneman, 1981).

Whilst Newell and Shanks somewhat counterintuitively suggest that the role of unconscious bias 'should not be assigned a prominent role in theories of decision making' (Newell & Shanks, 2014, P.2) – the vast majority of commentators suggest that bias, and particularly, unconscious bias is a material flaw amongst human agents. Kleinmuntz argues that the combination of cognitive limitation and prevalence of bias should lead the informed decision maker to use formulae where possible and their heads only 'very, very seldom' (Kleinmuntz, 1990, P.296):

> "Heads in this article's title refers to the processing of data clinically, subjectively, or intuitively; formula refers to its non-judgmental, mathematical, statistical, or mechanical combination" (Kleinmuntz, 1990, P.296).

Kleinmuntz follows a rich tradition within decision making literature citing illusory correlation, overconfidence, relevance of experience and cognitive overload as reasons to doubt the veracity of human, unaided decision making.

2.3.1 Part 1 Summary

Human agents use a combination of heuristics and intuition to make decisions in light of bounded cognitive capability and temporal limitations. These decision-making techniques depart from economic theory – resulting in decisions which are satisfactory rather than optimal. These short-cuts may serve as effective coping mechanisms – but can lead to a range of biases and errors in judgement. Although historically an abstract debate in the absence of alternatives, we believe there is an open question concerning the extent to which human unaided judgement should be applied in the presence of alternatives which may be less susceptible to such trade-offs.

2.4 Part 2: Organisational Decision Making

Organisations are fascinating arenas within which to explore decision making given that as Simon notes 'the task of 'deciding' pervades the entire administrative organization' (Simon, 1945, P.1). This point is reinforced by Fama who states:

> "Management is a type of labor but with a specific role – coordinating the activities of inputs and carrying out the contracts agreed among inputs, all of which can be characterized as "decision-making"" (Fama, 1980, P.290).

Jensen & Meckling suggest that most organisations are 'simply legal fictions' (Jensen & Meckling, 1976, P.310), in other words, artificial legal constructs that enable organisations to be theoretically abstracted from their agents and owners. As such we are encouraged to think about organisations as a 'nexus of contracts, written and unwritten among owners of factors of production and customers' (Fama & Jensen, 1983, P.302). Such organisations exist to 'meet the relevant marginal conditions with respect to inputs and outputs, thereby maximizing profits, or more accurately, present value' (Jensen & Meckling, 1976, P.307). Organisations then are complex networks of contracts between individuals – all of whom rationally seek to maximise utility through their behaviour, actions, and decisions.

Cyert & March (1963) challenged the traditional rational, economic theory of the firm. In much the same way as we have seen with utility theory. Economic theories of the firm consider that 'the objective of the firm is to maximise net revenue in the face of given prices and a technologically determined production function' (Cyert, 1963, P.4). The maximisation of such profit is achieved through the equilibrium position – establishing the optimum mix of product and factors. However, Cyert argues that firstly, profit maximisation is typically one amongst many goals of the organisation and that secondly, the '"firm" of the theory of the firm has few characteristics we have come to identify with actual business firms' (Cyert, 1963, P.7). The latter observation reflects the fact that the economic axioms assume that organisations operate with perfect information. The reality however is that firms must search and discover information. The nature and extent of that search has a material bearing on the decisions subsequently made – linking organisational decision making closely to both the theory of choice and the theory of search.

Cyert & March seek to address both a theory of firm and theory of organisation that provides predictive powers to understand organisational decision making:

> "Our conception of the task we face is that if constructing a theory that takes (1) the form as its basic unit; (2) the prediction of firm behavior with respect to such decisions as price, output and resource allocation as its objective, and (3) an explicit emphasis on the actual process of organizational decision making as its basic research commitment" (Cyert, 1963, P.18).

Organisational decisions can be considered as choices made amongst alternatives predicated on available information (Cyert, 1963). In this sense the authors encourage us to consider organisations as 'information processing and decision rendering system[s]' (Cyert, 1963, P.19). Recognising that individuals and collectives are likely to have different goals – we are invited to view the organisation as a coalition – which may in turn be comprised of sub-coalitions. The goals of organisations then are established through a process of accommodation and dialectic amongst coalitions. These goals are in a constant state of flux owing to 'disparate demands, changing focus of attention, and limited ability to attend to all organizational problems simultaneously' (Cyert, 1963, P.42). In contrast to economic theory – organisational 'searches for alternative courses of action constitute a significant part of non-programmed decision making' (Cyert *et al.*, 1956, P.247). Organisations conduct relatively limited search for alternatives, satisfice with available information and perform basic computation of relative merits. In such circumstances decisions are assessed on basic feasibility and financial hurdle rates – rather than returns relative to alternative choices. In certain situations this becomes 'a choice between doing something and at this time and doing nothing' (Cyert *et al.*, 1956, P.248). The latter constrained by both selective perception and recall – resulting in 'severe reality constraints or bias' (Cyert, 1963, P.80). Seen through such a lens, whilst organisations can be considered as information processing systems – they are far from optimal.

The foregoing is more than a little reminiscent of the accounts we have explored previously setting out the bounded rationality of individual human agents and the contradiction between economic theory of rationality and practical experience. As we have seen Simon (1945) highlighted that individuals are bounded in response to their cognitive limitations – with his work being broadly cited in organisational literature. However, Foss argues that his theories have 'been incompletely absorbed in the economics of organization, is little used for substantive purposes, and mostly serves as a rhetorical function' (Foss, 2003, P.245). Foss argues that although Simon made reference to the *administrative man*, the majority of his writing in relation to such bounded agents was negatively framed – or more specifically 'a basic problem with satisficing search is that there is virtually nothing in the theory itself about the merits of alternative search procedures' (Foss, 2003, P.257). In other words, Simon's theories suggest a problem – but without establishing a framework for how such issue might be addressed. Simon held three central tenants – that humans are cognitively limited, that agents attempt to address such limitations by relying on heuristic tools and that as a consequence such cognition and judgment are subject to a range of biases and often erroneous (Simon, 1945). Foss highlights that of these, economists have taken an interest in the first and broadly neglected the following two:

> "Thus, a broad implication is that paying more attention to such behavioural aspects allows for a richer understanding of the managerial task. In addition to performance assessment, the tasks of the tasks of the manager may also include correcting biases in judgement, curbing problems of procrastination and impulsiveness, influencing organizational expectations, and manipulating preferences" (Foss, 2003, P.260).

We concur that bounded rationality is incompletely explored and believe that rapid increases in automation provide a solid opportunity to revisit many of these principles.

That said, Dew et al correctly highlight that bounded rationality is a central tenant in Cyert & March's (1963) behavioural theory of the firm:

> "Central to BTF is the idea that decision making consists in finding a satisfactory solution (satisficing) rather than in evaluating the best possible alternative (optimization). Behaviourally speaking, management is therefore the art of dealing effectively with the reality of bounded rationality in a changing environment" (Dew *et al.*, 2008, P.38).

As a consequence we can conceptualise organisations as 'heterogeneous, boundedly rational entities' (Dew *et al.*, 2008, P.40). Thus, again, bounded rationality is considered an important topic in the theory of the behavioural firm - where decisions are made largely in accordance with standard operating procedures and through limited search for alternatives. Within organisations individuals are constrained or enabled through a 'learned set of behavior rules – the standard operating procedures' (Cyert, 1963, P.112). These standard operating procedures and rules of thumb are the dominant basis on which decisions are made – short cutting purely rational decision making. These decision-making principles are learned through experience and adjusted based on outcomes. Organisations thus develop routines and frameworks over time to assist in the decision-making process creating a 'source of change as well as stability' (Feldman & Pentland, 2003, P.94):

> "Routines consist largely of experiential knowledge, which may be tacit and hard to codify. Routines can be seen as successful solutions to problems that store and reproduce experientially acquired competencies, which can then be repeated over time" (Van Ees *et al.*, 2009, P.312).

These routines provide important sources of organisational learning and control – helping bounded managers to make better decisions – which both 'enable and constrain' (Van Ees *et al.*, 2009, P.312).

A common feature of such open corporations is the existence of a formal decision hierarchy that sets out the delegation of decision making and associated boundaries of agents' authority:

> "Decision hierarchies are buttressed by organizational rules of the game, for example, accounting and budgeting systems, that monitor and constrain the decision behaviour of agents and specify the performance criteria that determine rewards" (Fama & Jensen, 1983).

In addition to such formal monitoring systems open organisations also benefit from informal monitoring amongst agents – which occurs through day-to-day interaction – and is a natural consequence of agents serving their own self-interest through networking and self-promotion. Finally, however the 'common apex' of the decision control systems of large organizations is the board of directors – 'such boards always have the power to hire, fire, and compensate the top-level decision managers and to ratify and monitor important decisions' (Fama & Jensen, 1983, P.311).

Whilst the board limits the decision-making authority of senior agents within the business – one of the most significant challenges is the information asymmetry that exists with which to make and monitor decisions:

> "The board uses information from each of the top managers about his decision initiatives and the decision initiatives and performance of other managers. The board also seeks information from lower level managers about the decision initiatives and performance of top managers" (Fama & Jensen, 1983, P.314).

This information asymmetry is particularly marked if one considers that the majority of board seats are typically awarded to external agents. Such external agents are decision making experts, but who will likely have limited information on which to base choices, outside of that provided by the relevant management teams.

Much has been written about the role of boards in protecting shareholder interests (Fama, 1980). As Eisenhardt note somewhat cynically 'much of organizational life, whether we like it or not, is based on self-interest' (Eisenhardt, 1989, P.64). Portfolio theory suggests that the principal is likely to be diversified across a number of investments and as such 'has no special interest in personally overseeing detailed activities' (Fama, 1980, P.291). Hence principals appoint boards to safeguard their investment:

> "The board is viewed as a market-induced institution, the ultimate internal monitor of the set of contracts called a firm, whose most important role is to scrutinize the highest decision makers within the firm" (Fama, 1980, P.294).

We question the extent to which shareholders are best served where bounded agents make decisions that are 'good enough' (Van Ees *et al.*, 2009, P.312) and that support the delivery of 'satisfactory profits' (Cyert, 1963, P.9).

2.4.1 Part 2 Summary

Organisations can be thought of as decision-making systems. Economic theory would once again suggest that rational organisations seek to maximise utility or profit through such decisions. However, the reality of managing the so-called nexus of contracts and the fact that such organisations have neither perfect information nor perfectly rational decision makers, lead organisations to make decisions which satisfice rather than maximise. Agency theory suggests that both individuals and coalitions will be driven to maximise their own utility through decisions – which may not in all instances align with the principal. Organisations deploy techniques to curb self-serving agents through organisational routines, schedules of authority and oversight from the board. We question the extent to which automation may be deployed to make decisioning more effective for owners, to increase data transparency and to limit erroneous judgements.

2.5 Part 3: Machine & Automated Decision Making

As Agrawal et al observe 'the computer revolution has blurred the line between physical and mental tasks' (Agrawal *et al.*, 2018, P.2). Machines are able to process vast amounts of information and are not limited by 'cognitive processing capabilities' (Kleinmuntz, 1990, P.299). If we refer back to the economic definition of a rational agent – it is becoming almost unquestionable that such definition is closer to the programmatic methods employed by machines, who now have access to almost infinite processing power. Such machines have no need to deploy satisficing heuristics at the expense of completeness.[4] Bounded search conditions are unnecessary and there is no question of 'miserly' cognitive limitations inhibiting their ability to assess relative payoffs with objectivity (Jarrahi, 2018). The extent to which automation will displace or augment human decision making has been the subject of much discourse. As Jordan & Mitchell highlight 'we appear to be at the beginning of a decades-long trend toward increasingly data-intensive, evidence based decision making across many aspects of science, commerce and government' (Jordan & Mitchell, 2015, P.257).

Despite Jordan & Mitchell's assertion that we are at the beginning of the journey – decision support systems have been around for well over 60 years experiencing 'winters and springs' (Duan *et al.*, 2019, P.63) – with so called expert systems heralding a new era of automated decisioning since the 1970s. Expert systems were developed out of artificial intelligence research – but despite significant initial hype – have experienced a number of *winters* lasting

[4] That said, we note the use of heuristics as an AI technique.

for some twenty years. As highlighted by Lebovitz et al 'early attempts utilizing rule-based expert systems largely failed, given technical limitations at the time' (Lebovitz *et al.*, 2021, P.1502). However, recent advances in machine learning has reinvigorated progress in this space as affirmed by Jingyu et al who note that '40% of the effect of AI comes from machine learning' (Jingyu *et al.*, 2021, P.1460). As a consequence, now more than ever we may ask 'less and less 'Are they here to stay?' and more and more 'How and where can we use them effectively' (Simon & Newell, 1958 P. 4).

As Edwards observes 'definitions of an ES [Expert System] are a veritable mine-field' (Edwards, 1992, P.115). However, what is common amongst definitions is the notion of an automated system that substitutes for, or in some instances, augments the performance of a role historically performed by a human expert. The most common form of expert systems are rule-based (Duan *et al.*, 2019; Thornett, 2001). Such systems have historically been built from rules 'elicited from human experts by a human knowledge engineer' (Duan *et al.*, 2019). As observed by Autor et al:

> "A central observation by this paper is that effectively all current commercial computer technology engages in rules-based reasoning, that is procedural. There is little computer technology that can develop, test and draw inferences from models, solve new problems or form persuasive arguments – things that many workers do routinely" (Autor *et al.*, 2003a, P.8).

Rule based systems are well suited to structured or even semi-structured decision scenarios – but are perhaps less well suited to unstructured decisions (Edwards et al, 2000). This is a point expanded by Lee who highlighted that legacy construction of such systems resulted in a practical requirement that they be tightly bounded in 'closed worlds' (Lee, 1983). In other words such systems ignore those items outside of their boundaries – which 'do not lend themselves to precise formulation, and the underlying modes of reasoning are approximate rather than exact' (Zadeh, 2001, P.73). As Lu and Mooney outline - characteristics which highlight that a problem domain is a good candidate for expert systems include: the problem requiring expert knowledge, judgement and experience that can be codified and has a 'heuristic nature' (Lu & Mooney, 1989, P.268), that an expert can be identified to support the development of such solution and that the size and complexity of the expert system is manageable given practical constraints.

The challenge for developing rule-based systems is that as we have seen, human agents do not necessarily rely on wholly rational decision-making principles. Additionally, experts often struggle to describe how they make decisions – reflecting Polanyi's paradox:

> "For decades, organizational scholars have been investigating the social, tacit, and embodied nature of knowledge in knowledge work. This literature builds on sociological insights of Ryle (1949) and Polanyi (1958,1966) who disentangle the explicit aspects of knowledge from the tacit: aspects of knowledge that are socially embedded, learned through experiences, tied to the senses, and cannot be fully articulated" (Lebovitz *et al.*, 2021, P.1502).

To illustrate the point Simon cited chess grandmasters, who when questioned about how they determine their moves whilst engaged in time constrained, simultaneous play, answer, that 'it is done by "intuition," by applying one's professional "judgement" to the situation.' (Simon, 1987, P.59) Such experts hold various patterns in their memory which they recognise in practice based upon years of experience. When such patterns are matched to a given situation, they result in a chain of associations enabling decisions to be made in a rapid fashion (Bainbridge, 1983) Simon suggests that the range of such patterns for a chess grandmaster is in the order of 50,000 – roughly the same range as the vocabulary of college graduates. These patterns are referred to as 'productions' (Simon, 1987, P.60) Productions are broadly equivalent in practice to the pattern recognitions highlighted by Sage (1981) – and whilst there may be nothing irrational about their usage – replicating the same with rule-based systems is challenging. Thus, as Lebovitz et al (2021) note, the *know-what* of knowledge work is far harder to automate than the *know-how* – resulting in material unintended consequences in practice.

This point was picked up by Dreyfus (1972) in his book – *What Computers Still Can't Do*. Writing at a time when machines had yet to master chess, defeat the world champion at Go and were still struggling with advanced pattern recognition, Dreyfus offered a series of logical defences against automation. In order for a machine to equal human performance Dreyfus argued that machines must be able to distinguish the 'essential from inessential', 'use cues which remain on the fringe of consciousness', take account of context and 'situate the individual with respect to a paradigm case' (Dreyfus, 1972, P.128). Human agents are perfectly adapted to large world contexts as a consequence of being 'in-the-world' (Dreyfus, 1972, P.252):

> "A phenomenological description of our experience of being-in-a-situation suggests that we are always already in a context or situation which we carry over from the immediate past and update in terms of events that in light of this past situation are seen to be significant" (Dreyfus, 1972, P.288).

'Being-in' then is a function of having an organic *body* that is part of the physical world. Human agents 'are embodied beings that inherently exist in a web of relations within political, historical, cultural and societal norms' (Newman *et al.*, 2019, P.7). This is in keeping with both Simon (1956) and Todd and Gigerenzer (2001), the latter of whom describe ecological rationality as the 'adaptive behaviour resulting from the fit between the minds mechanism and the structure of the environment in which it operates' (Todd & Gigerenzer, 2001, P.728). Given the complexity of the real world, humans must be adaptive to the environment in which they seek to respond – an environment in which 'acting fast can be as important as being correct' (Gigerenzer & Goldstein, 1996, P.660).

Dreyfus suggests that this provides an epistemological defence against machines. For machines to match human performance there is an assumption that 'all knowledge can be formalised, that is, that whatever can be understood can be expressed in terms of logical relations, more exactly in terms of Boolean functions' (Dreyfus, 1972, P.156). This challenge is compounded by the fact that such information must be reducible to 'bits':

> "Since all information fed into digital computers must be in bits, the computer model of the mind presupposes that all relevant information about the world, everything essential to the production of intelligent behaviour, must in principle by analyzable as a set of situation-free determinate elements" (Dreyfus, 1972, P.156).

Given that context impacts interpretation Dreyfus suggested that such 'formalization is impossible' (Dreyfus, 1972, P.286):

> "Besides the technological problem posed by storing a great number of bits of neutral data, there are in the last analysis no fixed facts, be they a million or ten million, as Minksy would like to believe. Since human beings produce facts, the facts themselves are changed by conceptual revolutions" (Dreyfus, 1972).

Thus so called facts taken out of context result in an 'unwieldy mass of neutral data' (Dreyfus, 1972, P.281).

Finally, at least for our purposes, Dreyfus argues that ‘computers can only deal with facts’ (Dreyfus, 1972, P.290) and that man is the ‘source of facts’ (Dreyfus, 1972, P.290). Human agents learn over the course of their lifetime – thus ‘no fixed responses remain in an adult human being which are not under the control of the significance of the situation’ (Dreyfus, 1972, P.290). Thus facts are not static but rather iteratively created by a ‘being who creates himself and the world of facts in the process of living in the world’ (Dreyfus, 1972, P.291). Machines however, historically have had fixed responses and an inability to evolve through such ‘conceptual revolutions’ (Dreyfus, 1972, P.290). Thus, in summary, Dreyfus suggests that machines are limited by an epistemological fallacy that the world can be reduced to digital bits, independent of context and the flawed assumption that such facts are static. Humans by contrast are embodied organisms that are perfectly adapted to large world contexts as a consequence of existing in a world where facts are fluid, context dependent and understood through dynamic learned responses.

Machines have also ‘been known to suffer from the “frame problem” which describes the inability of algorithms to reason about and act on events they are not designed to handle’ (van den Broek *et al.*, 2021, P.1560). McCarthy & Haynes suggest that:

> “A representation is called epistemologically adequate for a person or machine if it can be used practically to express facts that one actually has about the aspects of the world” (McCarthy & Hayes, 1969, P.9).

The ability to express fluents becomes a significant challenge for a ‘generally intelligent programme’ (McCarthy & Hayes, 1969, P.35). These fluents operate in much the same way as Dreyfus’ situational context – thus, in order to suggest that “it is raining” one must understand where it is said to be raining and at what point in time:

> “If we had a number of actions to be performed in sequence we would have quite a number of conditions to write down that certain actions do not change the value of certain fluents. In fact with *n* actions and *m* fluents we might have to write down *mn* such conditions” (McCarthy & Hayes, 1969, P.31).

In other words, what human agents may refer to as a common-sense understanding of natural language in context, requires significant programming to replicate in machine intelligence. The dynamic nature of real-world situations and the impracticality of programming such potential states, limits machines to narrow environments.

However, in the years since publication, technology has advanced exponentially on both the hardware and software front. Software provides machines with purpose and direction, whilst hardware provides physical form. A raft of artificial intelligence techniques have been developed over recent years - with neural network programming mimicking the 'brains underlying architecture, constructing layers of artificial neurons that can receive and transmit information in a structure akin to our networks of biological neurons' (Lee, 2018, P.8). The purpose of such techniques is to 'build computers that improve automatically through experience' (Jordan & Mitchell, 2015, P.255). In contrast to the expert systems of old, these new techniques, rather than following traditional rule-based programming, enable machines to identify patterns from data and to use analytics and big data to improve recognition and learn from experience. Moreover, machines now have the ability to deploy a myriad of sensors enabling them to map their environment and use motion to interact and respond to stimuli:

> "The IoT enables physical objects to see, hear, think and perform jobs by having them "talk" together, to share information and to coordinate decisions" (Al-Fuqaha *et al.*, 2015, P.2347).

This combination of advanced programming and increasingly sophisticated, ubiquitous hardware has seen workers displaced from factories to fast-food kitchens and seen autonomous vehicles become a reality. As highlighted by Berente et al 'AI-enacted materiality does not stop at the digital only frontier; AI is increasingly also used for engineering physical matters' (Berente *et al.*, 2021, P.1442). In other words, machines increasingly extend agency over the physical world.

With sensors now able to convey vast amounts of information and software able to map spaces in three dimensions – machines are able perhaps for the first time to interact with the world in a way that is becoming equivalent to human beings. Thus, we argue that rapid technology advancement has resulted in machines that by any definition may now truly be said to be *in-the-world*. As Anderson (2017) highlights such machines are actually capable of interpreting the world in far more efficient ways than human beings. Describing the use of drones within construction to review work in progress across vast physical sites, Anderson comments that ''Reality Capture' – the process of digitizing the world by scanning it inside and out, from the ground and the air – has finally matured into a technology that's transforming business' (Anderson, 2017, P.1). As a consequence of technologies such as this and now commonplace home devices such as Amazon's Echo - machines are increasingly overcoming Dreyfus' primary defence against automation by being very much of, and in, the physical world.

In addition, in recent years machines have stretched beyond the closed world bounds described by Edwards (1992) enabled by machine learning. Historically human agents have benefitted from a unique 'ability to learn and adapt to new environment and challenges' (Duan *et al.*, 2019, P.68). As we have previously suggested, expert systems reliant on rule-based protocols, built by human knowledge engineers will always be constrained by the amount of time necessary to understand the rules to be applied, the extent to which a given expert is able to articulate the manner in which they inform their decisions and the number of scenarios to which such a solution can be applied.

Machine learning techniques enable machines 'that improve automatically through experience' (Jordan & Mitchell, 2015, P.255) to overcome such obstacles by enabling machines to learn from data sets and continually refine their own algorithms to optimise outcomes. Hamet & Tremblay suggest that there are three types of machine learning unsupervised, supervised and reinforcement - all of which enable machines to 'learn through experience' (Hamet & Tremblay, 2017, P.S37). Supervised learning contains both dependent and independent variables whilst unsupervised enables the identification of patterns using independent variables. Unlike human agents whose ability to learn from feedback can be tainted by bias and regret – machines will learn from mistakes in an unfiltered manner 'it can thus be argued that many roles involving decision-making will benefit from impartial algorithmic solutions' (Frey & Osborne, 2017, P.16). This potentially enables broader application of technology, reduces the closed world limitations highlighted by Lee and improves the commercial return on the associated investment in building such systems. As a consequence 'many developers of AI systems now recognise that, for many applications, it can be far easier to train a system by showing it examples of desired input-output behaviour than to program it manually by anticipating the desired response for all possible scenarios' (Jordan & Mitchell, 2015, P.255).

However, solving for one problem creates another. One of the advantages of traditional expert systems is that the nature of their design allows for a detailed understanding of the manner in which decisions have been made. However, as Berente et al (2021) highlight the combination of increasingly autonomous machines, coupled with advanced learning, results in a third inter-related characteristic, namely, inscrutability. The advantage of detailed rule-based systems is that, when operating efficiently, human agents understand exactly how each decision has been arrived at. Algorithms can then be tweaked and tailored by human agents to achieve desired results. In highly regulated environments such conditions are critical to adoption (Davenport & Ronanki, 2017).

As Rudin highlights ‘black-box machine learning models are currently being used for high-stakes decision-making throughout society, causing problems throughout healthcare, criminal justice, and in other domains’ (Rudin, 2018, P.1). The reference to black-box in this context points to the fact that where machine learning is deployed the explanatory powers of the associated decisions are difficult, or in some instances, impossible to understand. In recent years machine learning has been blamed for denying people parole (Wexler, 2017) and even more proximally much has been made of social medias use of these techniques. Facebook whistle blower Frances Haugen claimed that the company’s products ‘harm children, stoke division and weaken our democracy’ (Hao, 2021) by allowing automated algorithms which promote content via ungoverned machine learning algorithms.

Rudin suggests that such black-box models are driven by two principal causes – complexity and proprietary ownership. The former is predicated on the belief that complex machine learning can lead to better outcomes (Jarrahi, 2018) - a point disputed by Min and Lee (2005). However, ‘the belief that there is always a trade-off between accuracy and interpretability has led many researchers to forgo the attempt to produce an interpretable model’ (Rudin, 2018, P.3). The second reason driving black-box systems is perhaps more troubling. Decisioning systems are not cheap and can lead to significant competitive advantage for the owners (Bowonder & Miyake, 1992). Providing explanatory insight into how such systems work, can increase the chances of competitors reverse engineering and replicating core principles. As such, proprietors defend their intellectual capital by refusing to provide explanation and hiding behind the black-box. Wexler highlighted how the owners of Compas in the US, a proprietary system used to assess parole decisions, refused to provide insight into how such decisions were being made despite questionable outcomes. In the case of TrueAllele – a decisioning tool used to assist with forensic evidence – ‘a California Appeals Court upheld a trade secret evidentiary privilege in a criminal proceeding – for what is likely the first time in the nation’s history – to shield TrueAllele source code from disclosure to the defence’ (Wexler, 2017).

Ultimately machines are simply tools. It is a human decision as to where and how such machines are deployed and utilised. Underpinning the use of any tool that humans deploy to solve for a given problem is the expectation that it will perform in a certain way. Everyday tools such as hammers, screw drivers, kettles, pot, and pans all serve a known purpose and can be relied on to perform their function as intended to support a given outcome. Automated solutions are no different:

> "Previous research suggests that the decision to perform the job manually or automatically depends, in part, upon the trust the operators invest in automatic controllers' (Lee & Moray, 1992, P.1243).

However, in high-stakes decision making trust is hard earned and confidence easily eroded (Rempel *et al.*, 1985). Thus, trust is seriously undermined when explanation of how decisions made are unclear or unknown. As Muir comments an automated solution 'no matter how sophisticated or "intelligent", may be rejected by a decision maker who does not trust it' (Muir, 1987a, P.527).

As Edwards (1992) highlights decision support systems exist along a spectrum – acting as either assistant, critic, second opinion, expert consultant tutor or full automata. One of the central considerations in automated decision theory and practice concerns the extent to which machines should augment or displace human operators. Given the sheer breadth of decision scenarios there is not a single approach in this space and situations must be addressed on merit. Deep Blues defeat of Gary Kasparov in 1997 highlighted that technology had reached a point where no single human being enjoyed the cognitive capability to defeat a machine in the space. This position was reinforced with AlphaGo's mastery of Go. It would have been simple at that juncture to declare that machines were superior in such closed worlds to human agents. However, as Jarrahi (2018) highlights – so called 'centaurs' – combined teams of humans coupled with machines were more effective than machines alone.

Augmentation itself is by no means straightforward. As Bainbridge highlights the 'irony that the more advanced a control system is, the more crucial may be the contribution of the human operator' (Bainbridge, 1983, P. 775) – which may in itself expand rather than eliminate underlying challenges. As automation in these instances does not replace human labour – but merely changes its involvement it can result in unanticipated consequences and instances of misuse (Muir, 1987a; Parasuraman & Manzey, 2010). In much the same way as we have previously argued that trust is essential for machines to be adopted – the flipside of the equation is that a 'user may trust a decision aid more than is warranted' (Muir, 1987b, P.527). Parasuraman & Manzey refer to these downsides as human performance costs – highlighting automation complacency and automation bias as two material issues associated with augmentation models. Such complacency has been cited as a major cause of incidents in recent years.

Automation bias concerns instances where human agents become biased by the recommendations of their agents in place of exercising their own judgment – leading to errors of omission and errors of commission (Parasuraman & Manzey, 2010). Anyone that has used navigational tools will likely have some experience of both phenomenon – with recommendations often being accepted without question – resulting in dubious decisions in certain instances. This challenge is picked up by both Fugener et al (2021) and Daugherty & Wilson (2018) in their consideration of human and machine hybrid activities arguing that such interaction requires new fusion skills amongst human agents. The latter highlight that these skills entail rehumanizing time, responsible normalising, judgement integration, intelligent interrogation, bot-based empowerment, holistic melding, reciprocal apprenticing, and relentless reimagining. Whilst we do not intend to discuss each of these fusion skills here – perhaps the key take away is that putting a human in the middle of automated systems requires effort and retraining of operators to reimagine their place in a holistic system. This is much in keeping with du Plessis & du Toit who noted that human agents may 'experience skill inadequacies' (du Plessis & du Toit, 2006, P.362) if unable to assimilate appropriately with automated systems.

Machines are increasingly deployed in a number of sectors to aid decision making. In the field of medicine doctors increasingly use machines 'that can perform the more complex tasks of pathologists and, in some instances, with superior accuracy' (Jha & Topol, 2016, P.2354). Within the military the development and deployment of 'lethal autonomous weapon systems' (Horowitz, 2016, P.25) are becoming increasingly common. Whilst in many instances these machines provide insight to their human operators – companies such as Renaissance Technologies use algorithmic trading software to allow fully automated High Frequency Trading. When dealing with vast amounts of data there are few, if any human agents that are now able to match the pattern recognition of such machines. How much room is there in trading or diagnostics for human intuition, regret, and bias? In such scenarios machines are well suited to the task of making rational, consistent recommendations and decisions. Unlike human agents whose ability to learn from feedback can be tainted by bias – machines will learn from mistakes in an unfiltered manner thus 'it can thus be argued that many roles involving decision-making will benefit from impartial algorithmic solutions' (Frey & Osborne, 2017, P.16).

These rapid advances in the use of machines in medicine, the military, social care, and automated transport has given rise to two new branches of research – machine morality and machine ethics (Anderson & Anderson, 2007; Gill, 2020; Wallach *et al.*, 2010). As Malle highlights 'robot ethics encompasses ethical questions about how humans should design, deploy, and treat robots; machine morality encompasses questions about what moral capacities the robot should have and how these capacities could be computationally implemented" (Malle, 2016, P.243). As machines become increasingly autonomous they will become agents responsible for 'distributing the well-being they create, and the harm they cannot eliminate" (Awad *et al.*, 2018, P.59). We are rapidly approaching the point where machines may be called upon to decide who lives and who dies in certain situations - without recourse to a human agent. Machine autonomy, which underpins such advances, can be understood as the "ability to operate in dynamic real-world environments for extended periods of time without human control" (Bigman *et al.*, 2019, P.3). Overcoming "algorithm aversion" (Gill, 2020, P.6) will be necessary if machines are to be accorded such autonomy to make decisions. The ability to make consistent decisions without recourse to emotive responses could be a blessing or a curse. As Deng argues "logic is the ideal choice for encoding machines ethics" (Deng, 2015, P.26).

2.5.1 Part 3 Summary

Automation has accelerated exponentially in recent years. Whilst expert systems of old may have faced epistemological challenges – recent advances in machine learning have enabled machines to reduce reliance on human knowledge engineers. In parallel the vast array of sensors deployed has increasingly translated the physical world to bits and bytes. In such environments machines benefit from significant processing power and impartiality. Black-box techniques cause challenges and concerns in relation to trust and transparency – contributing to the burgeoning interest in machine ethics. Despite a rich literature on the use of automated decisioning in medicine, the military and transportation – we find that the organisational impact of such technology is currently underserved. Given the open questions we identified in Part 1 and 2 of our review we believe that this is a material omission. The impact of such automation on organisational decision making is worthy of further review given its ability to potentially displace and/or augment human agents.

2.6 Part 4: Automated Decision Making in Organisations

Given advances in other decision-making environments such as medicine, the military and autonomous vehicles – we might be forgiven for expecting to see far greater focus on the use of machines to augment or automate decisions in organisations. All else being equal – machines have the potential to support controls through automated workflow, to reduce information asymmetry by supporting the democratisation of data, to reduce search costs by providing actionable data insight and to support the administration of the nexus of contracts that underpins organisational structures. Given that these challenges have long persisted it is intriguing that relatively little has been written in concrete terms about the extent to which organisational leaders – including the board – are looking to embrace automated decision making to address structural challenges. This is an omission highlighted by Bailey & Barley (2020) and Berente et al (2021).

Decision Support Systems are not new. A rich literature exists from the late 80s reviewing such tools and the impact on both individual and group decision making. Tools range from simple fault trees (Fischhoff *et al.*, 1978) through to more sophisticated enterprise tools and methods (Hogarth & Makridakis, 1981). These tools are aimed at improving decision making effectiveness and bringing 'structure to ill-structured decisions' (Kottemann & Remus, 1987, P.135). Yet the literature is inconclusive as to the effectiveness of such tools on decision outcomes. Lenz and Lyles note that when planning becomes 'too rational, it is onerous, dysfunctional, and incapable of producing clear strategic thinking' (Lenz & Lyles, 1985, P.68). What is clear however is that such tools impact decision making behaviour leaving open the question as to 'what extent is the effort allocated to organizational decision making justifiable' (Hogarth & Makridakis, 1981, P.106). In recent years decision support has transformed on the back of advances in technology – seemingly inviting us to reconsider these questions. We have moved beyond simple decision support mechanisms to instances where machines are able to support decisions in more dynamic ways. Unlike historic tools, machines increasingly have the ability to augment human decision makers on the one hand but equally to displace through automation on the other.

Edwards et al (2000) reviewed organisational usage of expert systems at three different levels – namely operational, tactical, and strategic. Their findings suggest effective replacement at the operational and tactical levels of the organisation which tend to be highly repeatable and transactional. Such systems were less effective as a substitute at strategic levels – but such systems could still enable effective support – but were in such instances dependent on their users. Cyert et al highlight that decisions within organisations vary to the extent to which they are programmed. On one end of the spectrum decisions are 'repetitive, well-defined problems (e.g. quality control or production lot-size problems) involving tangible considerations' (Cyert *et al.*, 1956, P.238) which the authors argue lend themselves reasonably well to prescribed economic models of establishing best outcomes. These decisions contrast with the 'non-repetitive sort, often involving basic long-range questions about the whole strategy of the firm or some part of it, arising initially in a highly unstructured form' (Cyert *et al.*, 1956, P.238). The authors describe this spectrum of decisions as programmed at the one extreme and non-programmed at the other.

Expert systems used to substitute for a human agent improved efficiency – but did not necessarily result in the expected efficiencies, where used in a support or augmentation capacity. This is a point supported by Lu & Mooney who suggest that 'a firm has to select projects which are appropriate and cost-effective for ES [Expert Systems] technology' (Lu & Mooney, 1989, P.267). Many white papers have been produced by advisory firms highlighting the criticality of automation for business leaders – however as Duan et al note:

> "As most similar claims are not substantiated by measurable empirical evidence and rigorous academic research, it is difficult to know how, why and to what extent AI systems are being used and impacting on individual and organisational decision making and transforming organisations" (Duan *et al.*, 2019, P.68).

That said, Jarrahi suggests that artificial intelligence has penetrated many organisational processes – resulting in fears that 'smart machines will soon replace many humans in decision making' (Jarrahi, 2018, P.577).

Jarrahi (2018) goes on however to suggest that organisational decision making is typically characterised by complexity, uncertainty, and equivocality. The former of which can be ably assisted by machines whereas human decision makers have a natural ability to address uncertainty and equivocality. Complex situations 'demand the processing of masses of information at a speed beyond the cognitive capabilities of even the smartest human decision makers' (Jarrahi, 2018, P.581). Automated tools deploying modern techniques have the ability to crunch through vast data sets using brute force to inform decisions. However, equivocality, which occurs due to divergent interests of stakeholders – transforms 'decision making from an impartial, objective process (as assumed in an analytical, rational approach) into an inherently subjective and political process' (Jarrahi, 2018, P.581). Addressing these softer issues is a task well suited to highly adaptable, experienced human agents. As such a key capability of organisational leaders is the ability to convince stakeholders of a particular form of action and to establish compromise positions representing the most satisfactory outcome as opposed to the theoretically optimal or best. Davenport (2016) stated that:

> "These kinds of issues and trends can't be captured in data alone. It's certainly a good and necessary thing for strategists to begin embedding their thinking into cognitive technologies, but they also have to keep their eyes on the broader world" (Davenport, 2016).

Two themes emerge from this which we believe are worthy of merit – firstly, the notion that certain trends cannot be captured by data alone and secondly that strategic decision making requires understanding of broader contexts outside of a given decision domain.

Much has been made of the role of big data in decision making in recent years. Indeed 'the introduction of machine learning in organizations comes with the claim that algorithms will produce insights superior to those of experts by discovering the "truth" from data (Fügener *et al.*, 2021, P.1537). As we have highlighted previously, technologies such as the internet of things – has created a connected landscape of sensors that can now capture data in a myriad of formats:

> "The basic premise is to have smart sensors collaborate directly without human involvement to deliver a new class of applications" (Al-Fuqaha *et al.*, 2015, P.2347).

This data combined with sophisticated analytical techniques is enabling machines in certain instances to make decisions that historically would have been the domain of human judgement. Youyo et al highlight for example how computer models based on digital footprints outperformed human agents and have 'external validity when predicting life outcomes such as substance use, political attitudes and physical health' (Youyou *et al.*, 2015, P. 1036). Interestingly the authors suggest that human judgement may still be more suitable for describing traits that are less evident from digital behaviour. However, in the future how much human behaviour will be exempt from potential measurement? Given that the authors conclude that 'in the future, people might abandon their own psychological judgements and rely on computers when making important life decisions' (Youyou *et al.*, 2015, P.1039) – including partners and career paths – we might be forgiven for thinking that there may be little in the future not reducible to formula.

Ogiela and Ogiela highlight the role of cognitive economics to analyse the economic/financial situation of organisations and to 'reason about their current and future situation' (Ogiela & Ogiela, 2014, P.752). Whilst they do not inherently contradict the foregoing position – the authors point to machines analysing broader and more diverse data sets to help support traditionally strategic decision making. This is in keeping with Davenport who suggested that human agents should not become complacent about their mastery of strategic decision making:

> "particularly given that it's not as if we humans are really that great at setting strategy. Many M&A deals don't deliver value, new products routinely fail in the marketplace, companies expand unsuccessfully into new regions and countries, and myriad other strategic decisions don't pan out" (Davenport, 2016).

This is an area that we consider of particular import given that the acceleration of technology. Should organisations be embracing technology to support broader strategic decisions in order to better inform them? Although boards and their management teams may continue to hold the deciding vote – we question whether strategic decisions should be driven by greater data insight and transparency. As Zadeh notes 'humans base whatever decisions have to be made on information, that for the most part is perception rather than measurement based' (Zadeh, 2001, P.73) – measurements are precise whereas perceptions are fuzzy. By contrast we could argue 'that AI could be a 'perfect agent,' since it does not have intentions or goals that could deviate from its principal's goals' (Newman *et al.*, 2019, P.20).

2.6.1 Part 4 Summary

Decision support within organisations is not new – with a rich literature existing since the 1980s. However, automation is transforming the role of machines in the decision-making process. Organisational decisions can be thought of as operational, tactical or strategic (Edwards *et al.*, 2000) with repetitive, programmable decisions at the operational and non-repetitive longer term strategic decisions that are more critical to organisational strategy (Cyert *et al.*, 1956). Organisational decisions are marked by complexity, uncertainty and equivocality (Jarrahi, 2018) which calls for mix of hard and soft decisioning techniques. Organisational decision-making equally calls for both structured and unstructured data and with the internet of things and increased usage of smart sensors – this data is increasingly rapidly. Machines may be better suited to processing such data supporting better organisational outcomes. However, we believe that more detailed analysis of this phenomenon is required. This is particularly pertinent given that there appears acknowledgement that data is not sufficient to fully inform all organisational decisions. Specifically, we do not believe that the question of where and why organisations should deploy automated decisioning solutions has been adequately answered and the extant literature is somewhat dated given acceleration of automation in recent years.

2.7 Part 5. The Mangle

Thus far we have considered unaided individual human decision making, reviewed the context and nature of organisational decisions and explored the extent to which both are disrupted by advances in technology. Given the ability for technology to both augment and displace we can expect to see a tension resulting in both hopes and fears – with human agents on the one hand welcoming opportunities for greater efficiency and impact – but equally fearing the impact of such machines on both their livelihoods and decisions made. As we have commented, organisations are social entities, and a rich literature exists concerning resistance to change and the unanticipated consequences of poorly deployed automated solutions.

Pickering (1993) invites us to consider the relationship between machines, human agents and organisational contexts through the lens of a dialectic relationship of accommodation and resistance. Central to this epistle is the notion that the dialectic is temporally emergent in practice and calls for recognition of both human and material agency. Pickering highlights that traditional sociology of science is humanist in its outlook, identifying humans as the 'central seat of agency' (Pickering, 1993, P.560) neglecting agency that should appropriately be ascribed to the material world:

> "I think the most direct route toward a posthumanist analysis of practice is to acknowledge a role for nonhuman – or material, as I will say – agency in science. Science and technology are contexts in which human agents conspicuously do not call all the shots" (Pickering, 1993, P.562).

This traditional way of thinking about the world then results in an 'asymmetric distribution of agency – all to human beings, none to the material world' (Pickering, 1993, P.562). We consider this to be relevant for several reasons – firstly, such accommodation and resistance is likely to impact the pace and breadth of adoption – 'does IT shape organizations, or do people in organisations control how IT is used' (Rose & Jones, 2005 P. 19). Secondly, such a dialectic could result in unintended consequences as a result of emergent accommodations and thirdly, we believe that the notion of machine agency is worthy of consideration given recent advances in machine learning.

Pickering rejects the notion that we think semiotically about material agency and cautions against the ‘spell of representation’ (Pickering, 1993, P.563). Instead Pickering suggests that his aim is to understand the world as a ‘field of performative material devices’ (Pickering, 1993, P.563). Pickering suggests that whilst material agency should be taken as seriously as human agency – the former is ‘temporally emergent in practice’ (Pickering, 1993, P.564). As a consequence ‘no one knows in advance the shape of future machines’ (Pickering, 1993, P.565) owing to the interaction between agencies which emerge over time and cannot be fully anticipated in advance. Thus the collision of material and human agency results in a mangling through a ‘network of humans, artefacts and culture’ (Matthews, 2021, P.26).

Unlike semiotic representations of material agency – which imposes symmetry, Pickering highlights that the two forms of agency are fundamentally different. Human agency is governed by intentionality:

> “We humans differ from nonhumans precisely in that our actions have intentions behind them, whereas the performances (behaviors) of quarks, microbes and machines do not” (Pickering, 1993, P.565).

As Rose & Jones states ‘lacking intentions, they [materials] can only ‘behave’ where people ‘act.’’ (Rose & Jones, 2005, P.25) Human agents ‘construct goals that refer to presently non-existent future states and then seek to bring them about’ (Pickering, 1993, P. 266). Such intentions and goals should equally be considered as being constructed in temporally emergent cultural settings and responsive to resistance and adaption through modelling - ‘accommodation amounts, to a greater or lesser extent, to revision of plans and goals, to a revision of the intentional structure of human agency’ (Pickering, 1993, P.580). Material agency by contrast has no equivalent to intentionality. That said ‘as AI increasingly approximates human intelligence, it attains attributes formerly reserved for humanity” (Newman *et al.*, 2019, P.13).

At this point one might rightly question why this epistle merits space within a literature review about the future of decision making in organisations. A fair challenge which we will seek to defend. Pickering suggests that material and human agencies ‘are mutually and emergently productive of one another’ (Pickering, 1993, P.567). In other words, real world outcomes are created through a dialectic of accommodation and resistance – they are mangled:

> '"Mangle" here is a convenient and suggestive shorthand for the dialectic: for me, it conjures up the image of the unpredictable transformations worked upon whatever gets fed into the old-fashioned device of the same name used to squeeze water out of washing" (Pickering, 1993, P.567).

This mangling or 'brute emergent of resistance' (Pickering, 1993 , P.576) is an interesting lens through which to consider the interaction between machines, individual humans decision makers and organisational decision making. The process of developing automated solutions is an emergent process in which human and machine agency become 'inextricably intertwined' (Martini *et al.*, 2013, P.199) through practice:

> "Living in a world of ubiquitous networked communications, a world where AI technologies are interwoven into the social, political, and economic sphere means living in a world where who we are, and subsequently our degree of agency, is partially influenced by automated AI systems" (Newman *et al.*, 2019, P.9).

Leonardi (2011) suggests that where the perception of a machine is that it will constrain, actors will seek to change and resist technology whereas enablement or affordance will lead people to change their routines. Thus 'human agency is realized by both using the capabilities provided by technology and resisting the limitations those capabilities impose' (Leonardi, 2011, P.148). Resistance emerges at the intersection between human and material agency – transforming the former and thus 'materially structures human agency' (Pickering, 1993, P.581). In organisations automation will be embraced or resisted, deployed, or rejected and this dialectic is critical to understanding both potential breadth and scale of deployment – but equally organisational outcomes. As Charlwood & Guenole note optimistic and pessimistic accounts of automation are not mutually exclusive and as such a 'paradox lens suggests that the development of AI will be shaped by contradictory demands which will result in aspects of both co-existing' (Charlwood & Guenole, 2022, P.5).

There are several interesting themes for the purposes of our research. We question whether the acceleration of automation has in any way impacted the mangle of practice. Firstly, does the mangle effect outcomes at the operational, tactical, and strategic decisioning level highlighted by Edwards et al (2000)? In other words, is technology now being mangled further up the organisational chart – with lower-level work simply being displaced thus eliminating or reducing the need for accommodation and eliminating resistance?

> "When machines act they can be seen as tools (where they act directly under the control of humans to amplify their capacity to make a difference), as proxies (where they replace humans and act in their stead) or as automata (where they take over some (usually minor) part of human decision making as well as the power to act). Modern organizational computer systems can serve all three functions" (Rose & Jones, 2005, P.28).

In entirely closed loop systems – there is likely to be limited accommodation and resistance between man and machine – the machine is not dependent on the human actor and can exercise agency without resistance. This is a point highlighted by Berente et al who suggest 'contemporary forms of AI have an increasing capacity to act on their own' (Berente *et al.*, 2021, P.1437). In such instance the dialectic is simplified – human agents determine whether to deploy such solutions – but thereafter no further accommodation is required by a human agent – with no human in the middle. "People have agency and technologies have agency, but ultimately, people decide how they will respond to a technology" (Leonardi, 2011, P.151).

Secondly, we question whether the nature of material agency has changed in the thirty years since Pickering drew his distinction. With the advent of machine learning and the emergence of new and significant volumes of data - has the nature of intentionality been in any way impacted? Certain automation technologies are being given free rein to solve challenges using machine driven algorithms – advanced programming techniques allow machines to make decisions about data sources, validity and to deliver outcomes that have not been predetermined by a human agent – 'as machines have become more complex, their perceived autonomy increases' (Rose & Jones, 2005, P.27). This moves away from the notion that 'technology does nothing, except as implicated in the actions of human beings' (Giddens as quoted in Rose & Jones, 2005, P.22). We note that with increasingly connected devices:

> "these systems not only predict behavior based on observed similar patterns, they also alter the social fabric and reconfigure the nature of reality in the process. Through "personalized" ads and recommender systems, for example, the level and amount of options put in front of us varies depending on the AI's decision of "who we are," which reflects the place we occupy in the social hierarchy" (Newman *et al.*, 2019, P.11).

In a like manner Berente et al suggest that technology increasingly acts in 'new and surprising ways that are not necessarily delegated or dictated by humans' (Berente *et al.*, 2021, P. 1439). By any definition this moves beyond the realms of semiotic influence and is worthy of further exploration.

2.7.1 Part 5 Summary

We have acknowledged that organisations are social and political entities and as such we can expect to see both accommodation and resistance to new technology – particularly where such automation curbs behaviour and impacts power dynamics. Pickering's (1993) mangle of practice provides an interesting framework through which to consider the effects of such dialectic. We question the extent to which the mangle has been impacted in recent years – with displacement of tactical decisions and with augmentation moving further up the organisation hierarchy. We also question whether recent automation advances and in particular machine learning and black-box technologies has impacted the agency of machines.

2.8 Literature Review Summary & Open Questions

Our scoping literature review has explored several bodies of literature. At the risk of oversimplifying, we summarise the key themes in Table 1 below.

Key Themes
Bounded human agents (Simon, 1945) depart from rational principles of utility theory, using a combination of intuition (Evans, 2010) and heuristics (Todd & Gigerenzer, 2001) to make decisions often without conscious distinction, leading to bias and systematic errors (Tversky & Kahneman, 1974).
Organisations can be considered as information processing and decision rendering systems (Cyert, 1963) making decisions which are 'good enough' (Van Ees *et al.*, 2009) rather than optimal, as a result of heterogenous, bounded rationality (Dew *et al.*, 2008).
Agency challenges arise as organisations grow separating ownership from management. How do owners ensure that managers make decisions which maximise the principals utility (Cyert, 1963; Eisenhardt, 1989)? This issue is exaggerated by data asymmetry between owners and managers.

Key Themes
A raft of techniques have been deployed to address agency issues – with mixed success. Machines could potentially serve as perfect agents given that they cannot deviate from their principal's objectives (Newman *et al.*, 2019).
Machines, and in particular expert systems, have traditionally been used to address tactical and operational organisational decisions (Edwards et al, 1992; Cyert et al, 1956). Engineering bottlenecks (Frey & Osborne, 2017) and acknowledged epistemological challenges (Dreyfus, 1972; McCarthy & Hayes, 1969) have prevented further extension.
The automation of decision making appears increasingly advanced in certain industries – such as medicine, (Jha & Topol, 2016), transportation (Awad *et al.*, 2018; Bigman & Gray, 2018; Bigman *et al.*, 2019) and the military (Horowitz, 2016) – but appears more nascent in large organisations generally.
Recent advances in automation are driving a trend towards data driven, evidenced based decision making (Jordan & Mitchell, 2015). Machines are increasingly able to learn through experience (Hamet & Tremblay, 2017), but black-box techniques result in increasing levels of inscrutability (Berente *et al.*, 2021) and give rise to issues of trust (Muir, 1987b).
Technology deployment within large organisations can be considered as a dialectic of accommodation and resistance between human and material agency resulting in emergent outcomes in practice (Pickering, 1993).

Table 1: Literature Summary

The challenge with the extant literature is that technology has evolved significantly in recent years – rendering much of what has been written increasingly obsolete. Expert systems of old were confined to server rooms, entirely reliant on human knowledge experts translating the world into codifiable logic – resulting in well documented epistemological challenges and mixed business outcomes. However, with the advent of connected devices, digital operations, and machine learning, machines are now potentially able to overcome historical limitations. Whilst these new technologies give rise to a host of challenges related to explainability and trust, the availability of such computational capability must surely result in organisational leaders reconsidering where and to what extent to deploy such automation. Questions regarding machine agency, accommodation, and resistance in relation to the same, equally look set to evolve.

That said, given that our literature review was primarily conducted in 2019, and that a myriad of publications have been released in the intervening period, there is a risk that our research is already out of date. Moreover, it is possible that the issues identified above have been addressed in the intervening period. In an attempt to redress these issues, we reviewed a special edition of MIS Quarterly focusing on managing AI from September 2021. The Special edition highlighted a number of the themes identified within our literature review – adding credence to our work. Unsurprisingly, given the nature of information systems research – a multi-disciplinary approach is advocated to support the 'sociotechnical thinking' (Berente *et al.*, 2021, P.1445) required to adequately address research questions in this space. Decision making features prominently across all articles – highlighting inter alia the increasing autonomy of machines (Berente *et al.*, 2021), the critical role of machine learning (Berente *et al.*, 2021; Fügener *et al.*, 2021; Lebovitz *et al.*, 2021; Sturm *et al.*, 2021; Teodorescu *et al.*, 2021) and the challenges associated with inscrutable black-box technology (Berente *et al.*, 2021).

In the absence of universal truths concerning automation, the special edition highlights that one of the key challenges facing leaders involves making discerning choices regarding the deployment of technology (Berente *et al.*, 2021; Jingyu *et al.*, 2021; Lebovitz *et al.*, 2021; Sturm *et al.*, 2021; Teodorescu *et al.*, 2021). We note however that outside of advisory practices – limited practical guidance exists. Consequently, although technology looks set to transform organisational decision making, there is an open question regarding where and to what extent leaders should look to deploy technology to support decision making in large organisations. Motivated by this open question we go on to set out our methods in the following chapter.

Chapter 3: Methods

3.1 Introduction

Given the acceleration of automation and the potential impact of the same we concur with Saetre & Van de Ven that the 'need for generating new management theories that address problems or anomalies encountered in rapidly changing organizational and social contexts has never been greater' (Saetre & Van de Ven, 2021, P.3). As they go on to observe 'deductive, inductive and abductive reasoning each have a role to play in understanding the world' (Saetre & Van de Ven, 2021, P.3) – which is increasingly 'dynamic, interconnected and uncertain' (Saetre & Van de Ven, 2021, P.3). Whilst we acknowledge that much work has been performed in the fields of medicine, transportation, and the military – we believe that the impact of automation on decision making within broader organisational contexts is underserved in the existing literature. Given the emergent nature of this field we believe that abductive methods are most appropriate to support the generation of new knowledge. If deductive inferences are certain, inductive are probable and abductive theories are plausible – the latter is most likely to help us understand and frame the complex and ambiguous landscape that we seek to address at this early stage:

> "The world is very complex. There are no simple explanations for things. Rather, events are the result of multiple factors coming together and interacting in complex and unanticipated ways" (Corbin & Strauss, 2008, P.7).

We set out our approach and associated methods below.

In keeping with Leonardi who stated that 'ultimately, people decide how they will respond to a technology", (Leonardi, 2011, P.151) and Bailey & Barley who call for an examination of 'the interests, goals and perspectives of those who make or influence decisions about design and adoption' (Bailey & Barley, 2020, P.4) - we believe that the attitudes and practices of organisational leaders are likely to have a significant impact on the scale and scope of automated decision making. By leaders in this context, we refer to the board, the C-suite and those functional leaders responsible for running various operational aspects of organisations. Ultimately these stewards will determine where to invest and for what reasons:

> "It is the managers that make all key decisions about AI… Managers allocate resources, oversee AI projects, and govern the organizations that are shaping the future" (Berente *et al.*, 2021).

We believe that understanding the knowledge, attitudes and practices of such leaders will go a significant way to addressing the open questions we have identified. We equally acknowledge that such leaders do not exist in a vacuum and will likely be impacted by both advisory firms and by the service providers that exist to service such requirements. As such we acknowledge influence and 'power dynamics beyond the organization' (Bailey & Barley, 2020, P.7).

The established method of understanding the same would be to utilise KAP surveys. In traditional KAP surveys the 'knowledge part is normally used only to assess the extent of community knowledge' (Launiala, 2009 P.3; Wan *et al.*, 2016) about very specific scientific concepts. The assumption being that knowledge is based on 'scientific facts and universal truths' (Launiala, 2009, P.3). Whilst knowledge is in our instance perhaps less objective than would be the case in medical studies it is nonetheless acquired through both 'education and experience' (Wan *et al.*, 2016, P.4). Attitude 'is usually used to refer to a person's general feelings about an issue, object or person' (Launiala, 2009, P.4). Practices then relate to the tangible and measurable behaviours and actions of actors. (Launiala, 2009; Wan *et al.*, 2016)

It could be argued that the quickest route to solicit this understanding would be via a deductive approach – with KAP studies most often being supported by quantitative questionnaires - born out of family planning and population studies in the 1950s (Launiala, 2009, P.1). However, whilst the simplicity and surety of this route appeals - we acknowledge that the associated practices "presuppose that the questions asked make uniform sense to the people being surveyed and that the answers make sense." (Rubin & Rubin, 2016, Chapter 2, P.3) In other words, the approach requires a shared and common understanding of nomenclature and lends itself to a mature and well-developed field.

We have however, acknowledged that even the very simplest constituent concepts within our research area have 'broad meaning' (Agrawal *et al.*, 2018, P.3) and as such we cannot take for granted that our research subjects share a common understanding of such terms. In fact, it is expressly understanding how terms such as decision making, automation and judgement are construed in an organisational context that we are keen to examine. Not only would deploying quantitative methods make certain assumptions about shared language and understanding – but in extracting closed responses we would be denied the opportunity to probe further for nuance and meaning. Fundamentally, despite the obvious advantages of quantitative research in terms of clarity of conclusion – we do not believe that such an approach would generate meaningful new or practical knowledge at this stage. Further we acknowledge the criticism levied against the ability to measure attitudes via questionnaires (Launiala, 2009). Such criticisms can less readily be levied against qualitative methods given the inherent ability to take into account of contextual factors.

Underlying quantitative methods is a positivist theory that the researcher is neutral and has limited impact on what is being measured. However, given that as Rubin & Rubin highlights 'the researcher is human, not automation' (Rubin & Rubin, 2016, Chapter 2, P.3) the researcher inevitably affects what is learned and how it is interpreted. The irony of the foregoing is not lost on us given the subject matter of our research area! Organisations are comprised of people operating in socially, economically and political charged situations and to understand them we must explore 'peoples experiential life "as it is lived, felt, undergone, made sense of and accomplished by human beings."' (Schultze & Avital, 2011, P.1) We seek therefore 'to step beyond the known and enter into the world of participants, to see the world from their perspective and in doing so make discoveries that will contribute to the development of empirical knowledge' (Corbin & Strauss, 2008, P.14). Whilst we are mindful of bias and the impact of our own prejudice – we accept that it is an inevitability given the nature of the knowledge we seek and the nature of our methods.

3.2 Abductive Framework

In order to give structure to our research philosophy we have been guided by the four steps outlined by Saetre and Van de Ven in conducting 'disciplined imagination' (Saetre & Van de Ven, 2021, P.3) in support of abductive reasoning. The authors require scholars to follow a disciplined approach to the observation and confirmation of anomalies before generating and evaluating hunches. The authors acknowledge that in practice such steps may not be distinct and sequential but 'overlap, iterate and unfold in stochastic ways over time' (Saetre & Van de Ven, 2021, P.23). Adopting this approach has assisted in ensuring that our research despite being qualitative is rigorously grounded. The abductive process is characterised by 'disciplined imagination, evolutionary and dialectical interactions between individual and collective abduction, and social interactions amongst collaborating scholars' (Saetre & Van de Ven, 2021, P.23). We believe this is particularly relevant to the nature of a scholarly practitioner. Throughout the course of our research, we have been assisted by a supervisor, supported, and challenged by a cohort of peers and operated within an organisational context that has provided ample opportunity to discuss, develop and reflect upon ideas within an organisational context.

Further, we have found that research is not linear. Although we conducted an extensive narrative literature review before initiating our empirical work, had well-formed views of the nature of the questions we sought to answer and utilised a well-defined methodology – we find that the process has been iterative. At each stage in the development of our work we have looked across literature, considered methods in light of findings and begun to iterate our discussion. Although the narration of such activity within a paper makes the process appear linear, we acknowledge that the reality is anything but. It is this flexibility and dynamism that make abductive methods so appropriate for this type of research.

3.3 Anomaly Identification

Saetre and Van de Ven (2021) suggest that the 'starting point of abduction for management scholars is noticing an anomaly in fieldwork, data analysis, reading literature, or teaching when assumptions or understandings of existing models break down, and call for revisions or extensions' (Saetre & Van de Ven, 2021, P.9). This is a similar notion to that of problematization highlighted by Alvesson and Sandberg (2011) – who criticise traditional 'gap-spotting' (Alvesson & Sandberg, 2011, P.247) as being somewhat unambitious in its focus on simply critiquing literature - rather than fundamentally challenging underlying assumptions. It is suggested that the likelihood of identifying an anomaly is increased as a result of a number of factors including - cognitive flexibility and exposure to a breadth of experiences and literature. As a DBA student this method is particularly well suited to our work. As a scholar situated in practice we sit at the intersection between academia and practice. As we have reviewed the literature, we have been able to frame it against our lived experience in a large organisation. This is of course not a chance occurrence – given that we have reviewed the literature with such anomaly detection in mind – very much in keeping with the notion of a 'prepared mind of someone who is 'primed' to see something' (Saetre & Van de Ven, 2021, P.11). Our process has been somewhat iterative over several years.

Building on the key themes identified from our literature review we set out below a non-exhaustive list of anomalies in Table 2 below:

Key Themes	**Perceived Anomaly**
Bounded human agents (Simon, 1945) depart from rational principles of utility theory, using a combination of intuition (Evans, 2010) and heuristics (Todd & Gigerenzer, 2001) to make decisions often without conscious distinction, leading to bias and systematic errors (Tversky & Kahneman, 1974).	Given acknowledged limitations of human agents, agency related concerns and the seemingly increasing viability of inorganic alternatives – it is somewhat surprising and even counterintuitive that there continues to be such significant emphasis given to human decision making in large organisations.
Organisations can be as considered information processing and decision rendering systems (Cyert, 1963) making decisions which are 'good enough' (Van Ees *et al.*, 2009) rather than optimal, as a result of heterogenous, bounded rationality (Dew *et al.*, 2008).	
Agency challenges arise as organisations grow separating ownership from management. How do owners ensure that managers make decisions which maximise the principals utility (Cyert, 1963; Eisenhardt, 1989)? This issue is exaggerated by data asymmetry between owners and managers.	
A raft of techniques have been deployed to address agency issues – with mixed success. Machines could potentially serve as perfect agents given that they cannot deviate from their principal's objectives (Newman *et al.*, 2019).	
Machines, and in particular expert systems, have traditionally been used to address tactical and operational organisational decisions (Edwards et al, 1992; Cyert et al, 1956). Engineering bottlenecks (Frey & Osborne, 2017) and acknowledged epistemological challenges (Dreyfus, 1972; McCarthy & Hayes, 1969) have prevented further extension.	The exponential increase in connected devices, increasingly digital nature of

<table>
<tr><th>Key Themes</th><th>Perceived Anomaly</th></tr>
<tr><td>The automation of decision making appears increasingly advanced in certain industries – such as medicine, (Jha & Topol, 2016), transportation (Awad et al., 2018; Bigman & Gray, 2018; Bigman et al., 2019) and the military (Horowitz, 2016) – but appears more nascent in large organisations generally.</td><td rowspan="2">organisations, and machine learning look set to result in machines that are increasingly in the world and well adapted to supporting complex decision making. Given the prevalence of the same in certain industries it is perhaps surprising that there appears to be somewhat of a lag across other large organisations.</td></tr>
<tr><td>Recent advances in automation are driving a trend towards data driven, evidenced based decision making (Jordan & Mitchell, 2015). Machines are increasingly able to learn through experience (Hamet & Tremblay, 2017), but black-box techniques result in increasing levels of inscrutability (Berente et al., 2021) and give rise to issues of trust (Muir, 1987b).</td></tr>
<tr><td>Technology deployment within large organisations can be considered as a dialectic of accommodation and resistance between human and material agency resulting in emergent outcomes in practice (Pickering, 1993).</td><td>Technology appears to increasingly displace, reducing accommodation and resistance from directly impacted agents. Legislation, professional bodies, and customer preferences appear to be having a significant impact on deployment of technology.</td></tr>
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Table 2: Anomalies

3.4 Confirming Anomalies

The second stage in Saetre and Van de Ven's model involves confirmation of anomalies i.e. 'verifying that the anomaly exists' by presenting 'evidence and arguments' (Saetre & Van de Ven, 2021, P.11). The intention here then is to demonstrate that the anomalies occur with 'some regularity' (Saetre & Van de Ven, 2021, P.11) and to ground the same in evidence.

Saetre and Van de Ven highlight that disciplined ways to confirm the existence of anomalies include 'grounding and diagnosing the phenomenon' – which entails exploring the 'nature, context, and what is known about the phenomenon' (Saetre & Van de Ven, 2021, P.12). This can be achieved through reviewing literature and talking with people who have experience of the anomaly. Our early exploration of the identified anomalies entailed discussion and challenge with both supervisor, peers and we have been fortunate enough to test casually with industry experts as well as organisational leaders.

We return to our anomalies in Section 5.5, reflecting on the same in light of the results of our qualitative fieldwork.

3.5 Idea Generation

Saetre and Van de Ven (2021) suggest that once anomalies are firmly grounded that an abductive approach should lead to the creation of alternatives hunches that may provide possible explanations. Whilst we acknowledge the collective creative process advocated – given the nature of our endeavour we rely instead on the notion of 'trusted collaborators' (Saetre & Van de Ven, 2021, P.12). In this instance we have relied heavily on our supervisor to support the process and to provide challenge. We acknowledge that:

> "Most managerial topics and phenomena studied are complex and ambiguous because they reflect multiple dimensions, disciplines, and stakeholder perspectives that typically exceed the recognition skills of one individual." (Saetre & Van de Ven, 2021, P.18)

As we will highlight subsequently, disciplined coding has proven to be a useful technique for helping to identify patterns and themes in our research.

3.6 Idea Evaluation

We note Saetre & Van de Ven's (2021) final stage of idea evaluation. Within the discussion section of his document, we have set out our thoughts and perspectives based upon our identified anomalies, the extant literature, the results of our primary research and discussion with both our supervisor and others. We have used formal coding methods to review the data generated, as set out below. Our coding resulted in three aggregate dimensions that we have subsequently used to build a model for practice to explain and support the phenomenon identified.

The evaluation of this idea began with 'intimate partner[s]' (Saetre & Van de Ven, 2021, P.12) in the form of those that have been close to our research for several years. Our final step in evaluating our model entailed sharing the same in more 'public debates' (Saetre & Van de Ven, 2021, P.12). The foregoing recognises that the 'evaluation used by a single person is seldom effective' (Verganti, 2016 as referenced in (Saetre & Van de Ven, 2021, P.12). We detail in Chapter 6 the workshop held with two leading advisory firms which helped to refine our thinking and presentation.

3.7 From Theory to Method

The abductive process model set out above provides a useful reference for our research – although it stops short of providing an appropriate research methodology. In the following sections we set out in detail the research methods used to conduct and frame our qualitative field work. We acknowledge the criticism levied against both qualitative and abductive methods from the likes of Myers and Newman (2007) and in particular the design, conduct and reporting of such research. Whilst we do not enter a lengthy debate regarding the same – we believe that the combination of a robust theoretical framework coupled with an established and recognised methodology helps to provide transparency and promote credibility.

We acknowledge Roulson's challenge 'that novice researchers still struggle with making sense of how 'theory' relates to the interview method' and therefore the need to establish a 'theory-method connection' (Roulston, 2015, P.203). Whilst there is significant appeal to the neo-positivist theory that a skilled, neutral interviewer may reveal an *authentic self* that may not be publicly accessible – we do not believe that this would be revealed by any arts that we possess – given that by definition the majority of our interviewees are well versed in revealing only that which they are prepared to share. Years of facing off to shareholders, auditors, senior leadership, analysts, and other skilled interrogators is likely to have created effective defences. Nor do we believe that a purely neutral stance is practical to generate narrative discourse and generate the depth of insight that we seek. Thus, whilst the ability to access 'what is really going on', or what participants really think, believe, and do' (Roulston, 2015, P.217) is attractive – we are pragmatic enough to acknowledge that this is unlikely to be achieved through our work, unless participants are willing to share.

In a similar manner the romantic interviewer seeks to access the inner sanctum of the interviewee by generating a 'conversation that is intimate and self-revealing' (Roulston, 2015, P.217). In order to establish this rapport, the researcher must be prepared to share their interests and to readily express these in the discourse. However, for the reasons articulated previously – we do not believe that in the course of our interviews with senior, relative, strangers, that we will through any degree of empathy unpack these types of insight. We equally discount the notion of transformative interviewing – given that we do not seek to play an active role in transforming the views of our interviewees. We are interested in understanding perspectives – not altering them.

The constructionist concept of interviewing perhaps comes closest to our objective:

> "From a constructionist perspective, the interview is a social setting in which data are co-constructed by an IR and IE to generate situated accountings and possible ways of talking about research topics (Silverman, 2001)" (Roulston, 2015, P.218).

As such the interview provides a 'version of affairs' (Roulston, 2015, P.218) – and the mutual interpretation of the discussion becomes important – helping to frame understanding. Whether or not this enables us to access some inner truth is not hugely relevant for our purposes. What our leaders actually believe is perhaps less important that what they are prepared to share. Given the choice between accessing an inner or public voice, we would choose the latter – given that it is this voice and perspective which drives change and is acted upon by followers and the organisation.

3.8 Structure and Flexibility

As Gillham notes:

> "If interviews differ in their purposes, they none the less have a great deal in common. The main difference is the extent to which the interview is structured, and the degree to which the interviewee is allowed to lead' the content of the interview' (Gillham, 2000, P. 2, C1).

The most structured examples of interviewing lead to binary or short responses. Such an approach is well suited to an inductive endeavour. As we have highlighted, we do not believe that such rigidity would be beneficial in our area given its potential ambiguity and complexity. We are attracted to methods that offer a greater degree of flexibility but within an over-arching structure that allows for control over themes and direction. We acknowledge that to achieve this 'people may need encouragement to say what they think and a bit of 'steering' to set them in the right direction' (Gillham, 2000, P.11, C2). We equally, acknowledge Kvale's observation that interviewing is a craft 'that is closer to an art than to standardised social science methods' (Kvale, 1996, P.85).

3.9 Interview Framework

In light of the foregoing, and in order to ensure appropriate rigour in our research we have elected to apply an established framework – deploying the responsive interviewing technique advocated by Rubin & Rubin:

> "Responsive interviewing is what we have termed our approach to depth interviewing research. The responsive interviewing model relies heavily on the interpretive constructionist philosophy, mixed with a bit of critical theory and then shaped by the practical needs of doing interviews. The model emphasises that the interviewer and interviewee are human beings, not recording machines, and that they form a relationship during the interview that generates ethical obligations for the interviewr. In a responsive interviewing model the goal of the research is to guarantee depth of understanding, rather than breadth. The third characteristic of responsive interviewing is that the design of the research remains flexible throughout the project" (Rubin & Rubin, 2016, Chapter 2, P.10).

Similar to Corbin & Strauss's notion of a 'sensitive interviewer' (Corbin & Strauss, 2015, Chapter 2, P.9), the responsive interview model recognises that a relationship is necessary between researcher and interviewee and that 'who they are and how they present themselves' (Rubin & Rubin, 2016, Chapter 2, P.1) affects the research. We believe that the information that interviewees are willing to share is likely to be broadly equivalent to that, that they would act upon and stand behind in the real world. As relative amateurs, applying the rigour of a framework, will help ensure the credibility of our work and provide a suitable structure to follow.

In the sections that follow we outline our approach in light of the responsive interviewing framework.

3.10 Ethical Considerations

We acknowledge that 'as part of the developing relationship with the conversational partner, the researcher takes on deep ethical obligations' (Rubin & Rubin, 2016, Chapter 2, P.14). We find that Guillemin & Gillam (2004) provide a useful methodology through which to explore these potential issues which is complementary to the responsive interview framework we have chosen to adopt. The authors distinction between procedural ethics and ethics in practice provides a useful lense through which to assess implications – whilst their application of reflexivity serves to promote effective practice in the field. These lenses are complimented by the ethical framework set out by Piper & Simons (2005).

As Guillemin & Gillam rightly highlight, procedural ethics 'usually involves seeking approval from a relevant ethics committee to undertake research involving humans' (2004, P. 263). As a student at Warwick Business School our research falls under the remit of the school's ethics committee. We have followed the authors suggested approach that the form should be 'free of jargon' (Guillemin & Gillam, 2004, P.263) and whilst we cannot claim to being experienced in this regard – we have aimed to at least inspire confidence that our approach is well thought through and thorough in its theoretical base. The fact that we were granted approval on first review suggests that we achieved our objective.

Ethics in practice 'pertains to the day-to-day ethical issues that arise in the doing of research' (Guillemin & Gillam, 2004, P.264). We acknowledge the universal themes identified by the authors related to minimising harm, the importance of informed consent, protection of privacy, the principle of beneficence and the need to report with accuracy – each of which we seek to address below. This is in keeping with the good practice proposed by Piper & Simon who invite us to 'consider at the outset what ethical issues might arise' (Piper & Simon, 2005, P.59).

We note that the obligation to report interviews with a high degree of accuracy and to keep commitments made to interviewees as part of securing their time and trust. As such we made a small number of commitments to interviewees when seeking their active participation. Firstly, information provided would be anonymised in any public papers, unless expressly agreed otherwise. Anonymous in this sense means that we shall ensure that it is not reasonably possible to attribute quotations or perspectives back to interviewees through the descriptors (or otherwise) used to frame the statements. We have offered to provide a copy of any published works to the interviewees.

We believe that limited harm can come to the interviewee if the foregoing protocols are upheld. Whilst we acknowledge that such harm is often 'subtle' we believe that there is limited risk in our context. In practice leaders are well versed in framing sensitive statements with suitable precursors – such as 'between you and I' and 'in confidence' – signposting that such information is expressly not to be shared. That said, we acknowledge that certain interviewees, particularly those with whom we have an existing relationship and shared connections, made statements, and revealed insight that are sensitive in nature and could cause embarrassment if revealed. Given the anonymous nature of our research we will of course seek to ensure that no harm falls on our interview partners – but we certainly acknowledge the privileged position of interviewing senior thought leaders and the associated obligation of trust associated with the same.

In keeping with the principles espoused by Rubin & Rubin (2000) and Guillemin & Gillam we agree that:

> "Research is primarily an enterprise of knowledge construction… This is an active process that requires scrutiny, reflection, and interrogation of the data, the researcher, the participants, and the context that they inhabit" (Guillemin & Gillam, 2004, P.274).

As such, we acknowledge the positional power of both the interviewer and the interviewee, its potential impact on the conversational partners, and that 'influence is a two-way street' (Rubin & Rubin, 2016, Chpater 2, P.12). As the Chief Procurement Officer of a FTSE100 organisation we acknowledge that interviewees who are either current, or prospective suppliers may agree to participate in anticipation of future work, reciprocal commitment, or a feeling of obligation. Whilst it is not possible to eliminate this issue – to the extent practical – no consideration has been exchanged as part of the commitment. We have presented ourselves in abstraction from our day job – setting out clearly in introductory communications that the research is being conducted as an academic exercise and that we are not acting in our professional capacity. We have expressly not interviewed any individuals whose firm may at the point of discussion be pitching for work via a formal tender process.

Notwithstanding the foregoing, we do acknowledge the privilege of our position. We have been fortunate to secure interviews with a wide range of professional services experts. Without detracting from our previous ethical observations, we are pragmatic enough to know that certain access would not have been granted were it not for the fact that introductions have been facilitated in certain instances in light of our professional role. However, this ensures that our research is somewhat unique.

In a similar manner, we further acknowledge the positional power of certain interviewees. Given that the conversational partners work within organisations that could be considered target employers for the researcher – care must be taken. Interviewees – could eventually become interviewers in a very real sense! We believe that the careful adoption of the responsive interviewing framework and methodical approach outlined below has helped to minimise bias and influence that could otherwise negatively impact the outcome of our work.

In this context it is perhaps worth setting out what we have not committed to. We have not afforded the interviewee the opportunity to review our work ahead of publication. In a similar manner whilst we have faithfully transcribed interviews – we have not provided a copy of the transcripts for approval. A copy will be made available upon request for informational purposes. We have not provided information regarding fellow participants or shared perspectives as part of our interviews that might betray the confidence of any other leader. We have not agreed to any material consideration in return for granting the interview.

In conclusion, we are mindful of the ethical considerations of qualitative research and have adopted Guillemin & Gillam reflexivity framework and whilst the framework is not prescriptive we have sought to consider 'how [our] research intervention might affect the research participants before any actual research is conducted and consider how they would respond as a researcher in the sorts of situations that they can at this stage only envisage' (Guillemin & Gillam, 2004, P.277).

3.11 Responsive Interviewing

One of the primary attractions of the responsive interviewing technique is the flexibility that is inherent in the methodology:

> "Research design and questioning must remain flexible to accommodate new information, to adapt to the actual experience that people have had, and to adjust to unexpected situations" (Rubin & Rubin, 2016, Chapter 2, P.14).

Given the nature of our research area we believe that this flexibility has provided depth of insight. We are attracted to the notion that through continuous design we have been able to gather evidence and test emerging theories – and that deploying these with latter interviewees has helped to generalise theory and insight. The authors use of the descriptor *conversational* *partners* we also feel is particularly apt given the individuals we have targeted. In our experience, senior leaders react far better to conversation than to strictly structured, rapid-fire questions.

3.12 Target Conversational Partners

Rubin & Rubin invite us to consider the 'research arena as a theatre in the round and try to locate interviewees with different vantage points on what is going on at centre stage' (Rubin & Rubin, 2016, Chpater 4, P.4). This analogy aptly describes our approach. We acknowledge that the future of automation will not be determined in a vacuum by one group of people. The knowledge, attitudes and practices of different interconnected stakeholders will have a bearing on the future scale and shape of adoption. As advocated by Bailey & Barley (2020) we acknowledge factors external to the organisation.

Central to our research are the senior leaders of organisations and in particular those leaders with functional responsibility for areas traditionally associated with high degrees of decision making. Ancillary to this group are the advisory firms who provide perspective and insight and who are influential in helping shape the perspective of leadership groups. Additionally, no practical progress can be made without automation solutions and as such we believe that the service providers offering such products are likely to have a significant bearing on our research area. Finally, the attitude of the board within our target organisations is likely to have a material impact, as highlighted by Jingyu et al (2021) who note that 'board-level moderators are likely to shape AI orientation' (Jingyu *et al.*, 2021, P.1622). this is to be expected given that their primary purpose is to serve shareholder interests and thus ensure that the best possible decisions are made by their charges.

We have chosen not to focus on a particular industry – but rather to seek a purposeful sample. That said, the majority of our interviews have gravitated towards the service sector. We have limited our target conversational partners to those centred around large enterprises – those with revenues in excess of $500m USD. Such organisations will typically no longer be solely controlled by an individual owner and whilst there may be some debate - such companies exist to serve the interests of their shareholders and as such the leaders of such companies ought to be concerned with making the best possible decisions for their shareholders and for such decisions to be made in a transparent and justifiable manner. We accept that this is an assumption which we will need to test through conversation. In that regard we delineate against smaller, owner lead organisations, which ultimately exist to serve the primary shareholder thus reducing the complexity of the organisational decision-making process.

Within our target organisations we have focused on speaking with conversational partners who operate at the C-suite level. All of these roles entail making difficult organisational decisions on a regular basis. Ultimately these leaders are responsible to the board and their organisation's audit committees. Their knowledge, attitudes and practices will likely have a material impact on decision making protocols both now and in the future (Bailey & Barley, 2020).

Our assumption is that advisory firms will play a material part in determining the knowledge, attitudes, and practices of our target senior leaders. The likes of McKinsey, Deloitte, Boston Consulting, KPMG, PWC, Ernst and Young and other equivalent advisory firms provide insight and guidance to senior leaders on a regular basis. Thus, their own knowledge, attitudes and practices are likely to influence both our target leaders and others in equivalent roles. Thus, to the analogy aptly described by Rubin & Rubin (2016), whilst such individuals may not be centre stage - they will likely play an important part in the unfolding plot. As such we have targeted key individuals in these firms – complementing our target leaders by identifying individuals that play a central role in advising the associated industry – even if they do not advise the specific industry leaders themselves.

The aforementioned firms not only act for organisational leadership teams but also influence the board. We believe that a sample representation from this latter group provides additional insight. The board exists to provide governance over the leadership team to ensure, amongst other things, that leadership is acting in its shareholder's best interests. We acknowledged that access to such individuals would be challenging – but targeted the same, nonetheless. The interviews granted provide further depth of insight and we take comfort from Gillhams's observation that a 'general rule in research is that the easier it is to get data, the less valuable' (Gillham, 2000, P.11) it is.

We were interested in speaking to Chief Executive Officers and founders of organisations that are providing technology solutions to our target organisations. Whilst our target leaders have their own knowledge, attitudes, and practices, informed in part by their advisors and the board – equally they will be influenced by the prevailing market and available solutions. Ideas would remain abstract and ethereal without solutions to test and meet demand. As such both major service providers, start-ups and scale-ups are crucial components in shaping the future. We believe that understanding the perspective of this stakeholder group provides rich insight and helps to shape where they believe opportunity lies in the coming years. We equally believe that their perspective and narrative on use cases is worthy of analysis. Again, this approach is intended to demonstrate to our readers that we 'have interviewed to obtain different points of view and that when brought together these understandings provide a complete picture' (Rubin & Rubin, 2016, Chapter 4, P.5).

3.13 Sample Size

Given the time-bounded nature of our research we take comfort from the fact that Rubin & Rubin note that one does not 'need a vast number of interviewees to increase the credibility' (Rubin & Rubin, 2016, Chapter 4, P.4) of one's findings. This is much in keeping with Brinkmann who notes that 'qualitative interviewing distinguishes itself by its ability to get close to people's lives, not by including a huge number of participants' (Brinkmann, 2013, P.59). To that end we proposed interviewing in the region of 20 conversational partners – with 5 coming from our professional advisor community, 5 from the supplier community and 10 coming from the leadership community of our target organisations. Within the latter we included any board members that we were fortunate enough to gain access to. This number is in excess of the rule of thumb of 15 participants proposed by Brinkmann (2013). We believe that such sample provides purposeful representation allowing our intended abductive inference and 'to build a theory that has broader implications' (Rubin & Rubin, 2016, Chpater 4, P.5). Against our target of 20 interviews our final count totalled 25 as set out below.

3.14 Interview Duration

Whilst in an ideal world the duration of our interviews would be determined by the optimal time required to fulfil our design – we acknowledge that this is not practical given the nature of our time constrained target leaders. Getting time with our target interviewees was always going to be challenging. The optimal time request for our proposed interview duration was between 45 minutes and one hour. Less than 30 minutes would make it difficult to extract any depth – whilst requesting longer would significantly reduce uptake. As such we set a minimum of 30 minutes (including situations where the interviews were cut short for whatever reason) – but with no maximum duration. If conversational partners were happy to continue past the allotted time – then we saw little to be gained by stopping them – particularly given that this was seen as a sign of engagement with the subject and a proxy for the richness of the answers provided.

3.15 Design

Whilst Rubin & Rubin emphasise flexibility within their responsive interviewing framework – they are equally clear on the need for thoroughness and accuracy. The former principle requires 'investigating all the relevant options with care and completeness checking out facts and tracking down discrepancies' (Rubin & Rubin, 2016, Chapter 4, P.6). Accuracy, compliments thoroughness - entailing the careful and methodical documenting of how one obtains, records and reports what has been heard. We also note the emphasis on transparency capturing both the thoroughness of the design together with revealing the 'conscientiousness, sensitivity and biases of the researcher' (Rubin & Rubin, 2016, Chapter 4, P.11).

Our design follows the basic structure of the responsive interviewing conversational framework – orientating around main questions, follow-up questions and probes:

> "The main questions help you make sure you are answering you research puzzle; the follow-up questions and probes ensure you get depth, detail, vividness, richness, and nuance" (Rubin & Rubin, 2016, Chapter 5, P.1).

We acknowledge that experienced researchers will typically prepare half a dozen primary questions, expecting to ask no more than three or four. Given the nature of our conversational partners we considered it unrealistic to expect to tightly control the direction of the conversation and felt that follow-up questions and use of probes would be critical to extracting nuance, depth and vividness (Gillham, 2000; Rubin & Rubin, 2016).

Our authors identify three approaches to structuring responsive interviews. Of these we believed that the river and channel pattern is most suited to our undertaking:

> "In contrast, you choose the river and channel pattern where you want to explore an idea, a concept, or an issue in great depth, following it wherever it goes. You might never get to some of the main questions, because you followed up on one of them and then continued by following up on the follow-ups rather than asking other main questions. It is as if you picked a channel of a river and traced it wherever it went" (Rubin & Rubin, 2016, Chapter 5, P.15).

We believed that this approach would provide the greatest insight to our research area given the seniority of our interviewees and our own relative inexperience in strictly controlling the direction of such interviews. Whilst we wanted to ensure that the conversation addresses our themes, we believed the insight would be richer and more nuanced if we followed the natural flow and gently used probes to ensure the narrative remained on the matter at hand whilst filling in gaps and clarifying what was said.

Follow-ups play a prominent role in the authors description of their framework. However, we acknowledged upfront that follow-up discussions with our conversional partners would be unlikely to be granted and as such in the majority of instances the emphasis would be on using probes and follow-ups in the moment. We note the authors suggested techniques of probing: ambivalence; concepts that are implied but not stated; the missing middle; questions avoided or answered excessively; and the need to follow-up on hints and the need to get past the party line.

Whilst we adopted the responsive interviewing technique, we also acknowledge the complimentary work of Kvale (1996) who highlights six criteria for assessing the quality of an interview. The author highlights the importance of spontaneous, rich, specific, and relevant answers to questions - suggesting that such questions should be short - allowing for longer answers, which in turn can be followed up to clarify meaning. To this end the criteria suggests that in an ideal interview - meaning is interpreted in real-time, with understanding verified during the course of the interview rather than after the event. Finally, the interview should be a narrative in itself calling for little additional explanation or description.

3.16 Main Questions

Our design was intended to unpack the knowledge, attitudes, and practice of our interviewees in relation to the anomalies identified and open questions identified from our narrative literature review. We established an initial, nuanced set of questions for each of our target conversational partner groups. In keeping with the flexible design of responsive interviewing we expected to iterate these questions.

We started each interview by reminding each interviewee about the nature of our research, highlighting that we were looking to understand the knowledge, attitudes and practice of senior organisational leaders, advisory forms, service providers and the board. We proposed that questions would be conversational rather than formally structured. Following this brief introduction and scene setting the vast majority of interviewees then launched into an account of what they were seeing in practice. Our questions differed slightly case by case predicated on the direction of the conversation but were loosely based around the questions set out in Table 3 below.

C-suite	Service Providers	Advisory	Board
• What trends are you seeing in relation to the automation of decision making within your organisation? • What role do you believe judgement plays in organisational decision making and is the situation changing? • How would you define judgement? • What automated decisioning use cases are you currently either considering or delivering?	• What work are you doing with clients in relation to the automation of decision making within your organisation? • What role do you believe judgement plays in organisational decision making and is the situation changing? • How would you define judgement? • What automated decisioning use cases are you currently supporting your clients to evaluate and deliver?	• What work are you doing with clients in relation to the automation of decision making within your organisation? • What role do you believe judgement plays in organisational decision making and is the situation changing? • How would you define judgement? • What automated decisioning use cases are you currently supporting your clients to evaluate and deliver?	• What trends are you seeing in relation to the automation of decision making within the organisations you support? • What role do you believe judgement plays in organisational decision making and is the situation changing? • How would you define judgement? • What automated decisioning use cases are you seeing from your senior leadership teams?

• Is your expectation that you will see a greater degree of data driven decision making going forward? • Do you consider decision making to be a hard of soft skill? • What if any limitations do you see in potential of machines to make decisions? • Do you see machines displacing or augmenting human agents? • Do you perform any post decision analysis?	• Are you seeing an increase in demand for solutions that support data driven decision making? • Do you consider decision making to be a hard of soft skill? • What if any limitations do you see in potential of machines to make decisions? • Do you see machines displacing or augmenting human agents? • Do you perform any post decision analysis?	• Are you seeing an increase in demand for solutions that support data driven decision making? • Do you consider decision making to be a hard of soft skill? • What if any limitations do you see in potential of machines to make decisions? • Do you see machines displacing or augmenting human agents? • Do you perform any post decision analysis?	• Do you expect to see an increase in data driven decision making in relation to decisions brought for board approval? • Do you consider decision making to be a hard of soft skill? • What if any limitations do you see in potential of machines to make decisions? • Do you see machines displacing or augmenting human agents? • Do you perform any post decision analysis?
In addition to the primary questions above – depending on the nature if the discussion we used to probes to explore the following areas when the conversation allowed it: • Generic AI – extent to which interviewers were aware of the concept and believed it is achievable			

• Bias – extent to which it impacts organisational decisions and likely impact of automation on the same • Regret – extent to which regret factors into decisions • Use cases – examples and knowledge of specific automation use cases

Table 3: Primary Interview Questions

3.17 Enlisting Interviewees

Linkedin provides a great method of keeping in touch with extended members of one's network and was used as our primary source of contacting potential interview targets. We identified leaders within our network that met our parameters and sent introductory emails requesting support. Emails were short and to the point – given that our target interviewees are senior individuals with limited time. We have included a sample introductory email in Appendix II – although these were tweaked for the recipients already known to us. Where we had personal or business emails for individuals, we sent emails directly.

In total we sent out 37 emails requesting time. Of those, 8 did not respond. We failed to find suitable time with a further 2 leaders. Within the 37 emails sent we wrote to 3 advisory firms and 5 service providers. These emails were sent to account leads with a request that we be introduced to individuals within the firm responsible for intelligent automation. The only organisations that we withdrew from were corporate brokers. We discovered that these organisations have strict protocols regarding interviews and confidentiality requiring that we send questions in advance and would have been far more formulaic than our other interviews. Of the 25 interviews conducted, 12 were with individuals who were previously unknown to us. None of our interviews were held with individuals from our own organisation.

3.18 Medium & Format

The lockdown resulting from the pandemic served us well with our research. Firstly, due to the lack of travel and commuting time both ourselves and our conversational partners were perhaps more accessible than would have otherwise been the case. Secondly, all meetings were conducted virtually. Virtual meetings lend themselves well to the conversational nature of our method – with video calls providing the ability to read body language and expression – but without the necessity to meet in person. Microsoft Teams was used to conduct meetings. Initially we took advantage of the technology to record and transcribe the meetings – but quickly moved to voice recordings and alternative transcription methods as set out below. The format also worked well with non-UK domiciled partners.

3.19 Transcription

We note the various transcriptions approaches adopted by researchers – ranging from short form notes through to full verbatim transcriptions including descriptive accounts of body language and form. For our purposes we wanted to ensure that we accurately captured language. We were less concerned with reflecting body language and tone – unless it was particularly relevant to the point being made. As an example, in virtual meetings conversational partners may gesture upwards or downwards to emphasise a point or indeed laugh whilst making an observation. Where such gestures were important to understanding they were captured – but otherwise we believe the narrative itself was sufficient for our research purposes.

Our initial approach to transcription was to record meetings in Microsoft Teams and use the automated transcription feature. We quickly established through our pilot interviews that such a process was suboptimal, given the technologies inability to adequately capture discussion - resulting in a laborious process of editing and validation. As such we adapted our approach – using an online subscription service (Transcription Puppy) – notably providing services to Barclays, Comcast, and NASA amongst others. The service enabled us to upload audio files and within 48 hours to receive a manually created transcript. Whilst the service failed to meet the 99% accuracy claimed and required manual adjustment – it materially accelerated our ability to create accurate transcripts.

3.20 Pilot Interviews

We began our interview process with pilot interviews. Whilst the conversational partners met our criteria – they were well known to us and thus likely to be somewhat more forgiving than relative strangers with whom introductions had been facilitated. The pilot interviews afforded the opportunity to test the conversational techniques that we were looking to deploy more broadly, to assess the quality of transcripts and to review the resultant content. Our intention was to use the output of these interviews as part of our research unless the experience resulted in poor quality data.

We quickly found that the conversational and open nature of our questions resulted in a rich dialogue and that conversational partners revealed the most interesting insights when left to talk – often using stories and examples to illustrate the points they were seeking to make. As expected, conversational partners were articulate and as such limited clarification was required to understand both the essence and nuance of the points being made. Early interviews lasted for around 60 minutes. We found that conversational partners found the topic engaging and keeping the discussion flowing was relatively straightforward.

The transcripts of our pilot interviews were shared with our supervisor to review the quality and depth of data generated. We felt the quality of the output was sufficient for our purposes and that no major alterations were required to the core method and approach. One of the things that quickly became apparent however was the length of time required post interview to create an accurate transcript and to code the same (see above).

3.21 Sample Transcript

It is not practical, nor useful, to provide a copy of all 25 transcripts. We have however provided a sample of one discussion in Appendix III hereto. In order to protect the identity of the leader we have redacted company names and any references to individuals. The leader interviewed is a member of the C-suite within a large, global pharmaceutical, has worked as a visiting lecturer at Oxford University and worked closely with Richard Susskind on the future of the court system in the UK. The transcript makes interesting reading.

3.22 Interview Overview

We conducted 25 interviews over a period of 9 months. These interviews resulted in over 170,000 words once transcribed. An anonymised list of interviewees is set out below:

Title	Company
CFO	Rank Group
CFO	LivaNova
COO	First Derivatives
CHRO	MGM
Founder & CEO	Qantx
Global Head of Credit Review & Analytics	JPMorgan Chase
Partner - Tax	Azets
Chief Product & Technology Officer	Conde Nast
Senior Vice President & General Counsel	GSK
Head of Strategy	Allegis Global Solutions
CIO	Santander
CFO	Seaborg Technologies

Table 4: C-suite Leaders

Title	Company
COO & Partner - QuantumBlack	McKinsey
Partner - Emerging Technology	EY
Partner - Digital Controllership & Risk Advisory	Deloitte

Table 5: Advisory Partners

Title	Company
Global Head of AI Solutioning	Cognizant
Partner - Cognitive Process Automation	IBM
Managing Director - Analytics Delivery	Accenture
Global Head of Responsible AI	Accenture
Global Data Science & Machine Learning Engineering Lead	Accenture
CEO	AltViz

Table 6: Service Providers

Title	Company
Non-Executive Director	Money Supermarket, Smith & Nephew and Aston Martin
Non-Executive Director	DMCC, International Chamber of Commerce, National General Insurance & HSBC
Non-Executive Director	Nationwide
CxO advisor & coach	BBC & Pearson

Table 7: Board Members

3.23 Coding

Our interview transcripts totalled in excess of 170,000 words. These transcripts were loaded into NVivo and coded to identify themes using the method advocated by Gioia et al (2012). Our interview transcripts are extremely dense and thus our 1st-order analysis which intended to 'adhere faithfully to informant terms' (Gioia *et al.*, 2012, P.20) resulted in a unwieldy list of some 108 codes. In keeping with Gioia et al we certainly can relate to the sentiment that 'you gotta get lost before you can get found' (Gioia *et al.*, 2012, P.20). Given the impracticable number of codes resulting from our initial effort we sought to reduce this list to a more workable number. By exploring similarities and differences in responses, and ruthlessly prioritising those insights that we considered to be most impactful for our endeavour – we determined 31 level 1 codes – as set out in Table 8 below.

Level 1 Codes
Adoption of automation more pervasive to augment human decision making in business-critical functions - results in 'human in the middle'

Level 1 Codes
Data volume and type - both structured and unstructured - increasing rapidly leading to new opportunities to exploit
Certain data sets are objective and irrefutable
Data fuels automation of decision-making process - requires effective data strategy
Organisational decisions require ability to make decisions using both hard and soft skills
Machines perfectly adapted to impartial, superior decision making where data is sufficient to drive insight
Human cognitive limitations make them ill-suited to data driven decision making across vast data sets
Range of organisational resistance to automation including algorithm aversion, reduced autonomy and power of human agents, fear of displacement (micro and macro) and lack of understanding
Automation inhibitors include compute, organisational complexity, data privacy, holding machines to higher standards, lack of compulsion from leaders, lack of data, legacy technology debt and human talent
Government and regulatory bodies impacting pace and breadth of automation adoption - limited tolerance for black-box
Increased focus on ethical and moral issues associated with automation
Trust and explainability key adoption issues for automated decision making
Human decision makers rely on intuition, gut instinct and experience which is difficult to articulate and thus to automate
Automation most adept at tackling specific use cases, fails to scale across contexts - resulting in proliferation of pilots - not all of which have a compelling business cases
Businesses are complex social organisations comprise a myriad of decision points
Human judgement, experience, and ability to contextualise is highly prized within organisations and certain professions - despite wide acknowledgement of bias
Human to human interactions and associated soft skills difficult to automate
Despite cognitive limitations - humans are adapted to deal with decision making in limitless contexts
Judgement, whilst highly prized, is an intangible mix of traits and hard to assess
Perception that not all decisions are reducible to tangible data points

Level 1 Codes
Stakeholders divided on preference for outcomes versus robust decision-making process
Human decision makers can manipulate data, relationships, and decision-making process to drive their own interests
Leaders have to pick their battles over decisions and may support those that they are not comfortable with
The future is difficult to predict, hard to reduce to data and necessary to support most complex organisational decisions
Automation enablers include specialist skills, education, 'full stack' & hybrid engineers, effective change management and agile approach
Automation can increase data transparency and democratisation of data
Significant range of adoption drivers including distributed expert knowledge, applicability in face of exhausted traditional levers, full population testing, response to scale and complexity, cost reduction, reallocation of resources, empowerment, and revenue generation
Expectation that organisational decisions will increasingly be data driven given superior outcomes
A lack of data transparency reduces effective governance of major decisions
Increasing acceleration of automation - varying materially by industry and function
Organisation adoption curve is slow and basic in many instances
Organisational decision making exists along a spectrum from tactical to strategic - automation is moving left to right - displacing at tactical level and augmenting at strategic level

Table 8: Level 1 Codes

Our 2nd-order analysis sought to question 'what's going on here' (Gioia *et al.*, 2012, P.20). This was an iterative process over a period of time and performed in conjunction with revisiting the extant literature and the open questions originally identified. At the final count we identified 10 2nd-order themes as set out in Table 9 below.

2nd Order Themes
Acceleration of displacement at tactical level will increase whilst increasing expectation of automated decision support at strategic level

2^{nd} Order Themes
Data volume and type - both structured and unstructured - increasing rapidly and leading to new automation opportunities to exploit
For the foreseeable future organisational decisions will continue to require a mix of hard and soft skills
Machines perfectly adapted to impartial data driven decision making and support in narrow contexts
Organisational resistance and inhibitors will continue to impact adoption, pace and impact of automation
Continued government, regulatory and professional body resistance to automation, increased focus on ethics
Trust and explainability will be material to adoption of automated decision making - transparency will be key
Increased expectation that data driven insight will be used to reduce human manipulation, bias, promote transparency and enhance decision making
Most challenging organisational decisions will remain those associated with predicting the future and capital allocation - in which situations human judgement and experience will continue to be highly prized
Organisational drivers will see automation accelerate and increasingly encroach from tactical to strategic decisions as expectation of data driven decision making and transparency increase

Table 9: 2nd-Order Themes

Finally, we looked across these identified themes to identify 'aggregate dimensions' (Gioia *et al.*, 2012, P.21). Again, we adopted an iterative process in this regard and our thinking was far from linear. In parallel with developing our coding we constantly revisited the literature. Whilst the write up of this method section may create the illusion of sequential thinking – the reality is that the entire process was hugely iterative. Our three aggregate dimensions are set out in Table 10 below — noting that it's a 'static picture of a dynamic phenomenon' (Gioia *et al.*, 2012, P.22). The aggregate dimensions highlighted below served as a useful framework when writing up our results in the section below.

Aggregate Dimensions
Data fuels the automation of decision making
Human judgement and experience continue to be valued in relation to high-stakes decisions requiring human interaction and/or projections of the future
The nature and form of accommodation and resistance to automation evolving

Table 10: Aggregate Dimensions

3.24 Feedback Workshop

As highlighted previously, in keeping with Bailey & Barley (2020), we believe that advisory firms and service providers play a major role in influencing senior leaders - helping to set the tone and direction of both the critical challenges facing business and the manner in which they are addressed. As such we considered that a good test of our proposed model would be to workshop the same with senior members of advisory firms who operate in and around the automation space. Much like our overall approach to qualitative research our emphasis was on depth, insight, and expanded narrative. As such we proposed running a feedback workshop for an hour with three advisory firms to present our proposed model for practice. We elected not to perform individual feedback sessions favouring a group discussion – which we felt would result in a more interesting debate. The fundamental purpose of the workshop was to determine the extent to which our model could be used in practice.

We issued three invitations to partner level individuals who had participated in our initial interviews and whom we felt had expansive and challenging views on our research area. We were pleased with the response. Despite the seniority of the people we approached – all three responded within 48 hours - consenting to participate. Setting a date was somewhat more challenging – trying to get 4 senior individuals together at the same time, even for an hour, is a logistical challenge. Without administrative support it would have been a very time-consuming process. In a similar vein, one of the biggest risks with the workshop was that it simply wouldn’t happen. Despite good intent, executive diaries are dynamic, and as such there was always the risk that it would constantly shift as diaries moved. In the final synopsis one participant withdrew with apologies two hours before the meeting, having been called to client site.

In anticipation of the workshop, we created a supporting presentation in PowerPoint – which was issued a week ahead of the session. The deck is set out in Appendix IV. In addition, we also provided a number of questions that we wanted to cover during our discussion. The presentation itself had to strike a balance between being sufficiently detailed to inform the discussion without resulting in information overload. Given the audience it also needed to be professional in appearance and tone.

The workshop itself was held over Microsoft Teams and was both recorded and transcribed with participant consent. The transcription process served as another reminder that technology is not perfect, and the effort involved in faithfully transcribing a session of any meaningful length is considerable.

The format of the workshop entailed ten minutes of presentation of the model and associated background to set the scene. Ten minutes is a challenging length of time to present four years' worth of work – but necessary in order to allow sufficient time for the substantive element of the discussion. It would have been inappropriate to assume that participants had read, digested, and fully understood the model in advance. Equally, condensing what could easily be an hour-long presentation to ten minutes served as useful motivation to consider what really mattered for time constrained leaders in practice.

In keeping with our interview approach, we did not want to be overly structured in our facilitation of the discussion. We have found that the most interesting discussions emerge when a theme is presented and then naturally flows. We were prepared to bring conversation back on track if it drifted and were particularly interested in examples. Ultimately, the most important question we sought to unpack was whether the model would have utility and impact in practice.

Our intention post workshop was to amend our model based on material feedback. For a model to land with impact it must be couched in an accessible way and resonate with the intended audience. As with all such things – models improve over time and thus we were conscious that what we were presenting was Version 1.0 of our model. Iteration and adaptation is important to ensuring ongoing relevance in a dynamic world.

The transcript from the workshop can be found in Appendix V and a summary of the resultant outcome can be read in Chapter 6 of this paper. We consider the workshop to be interesting from a number of perspectives. Firstly, the content itself is fascinating, providing real depth and practical insight into our research area. Secondly, it is highly unusual to have competing advisory firms talking in an open manner about a shared challenge. As can be seen from the transcript – the participants got on well and naturally collaborated and expanded on each other's thoughts. The resultant discussion was richer and more nuanced than it would have been had the discussions been held one on one. Thirdly, the workshop resulted in a number of important observations that have helped refine our work. Finally, as we have commented elsewhere, access to such individuals is rare. We are hugely fortunate that we can leverage our network to reach such individuals and remain grateful for their active participation. Again, we reiterate that the resultant findings are unique in academia.

3.25 Worked Example

In order to fully illustrate the practical application of our model we set out a worked example in Section 7.7. Using a subset of our own team within a FTSE100 organisation and targeting a discipline we know well, procurement, we create an illustration of the diagnostic application of our tool. The example is intended to be illustrative, not exhaustive. To create the example, we workshopped the model with members of our leadership team identifying decisions within the procurement domain before mapping against our model. We then overlay available solutions using a publicly available solutions map. Further details follow in Chapter 7.

3.26 Lessons Learned

Before moving on to summarise our results – it would be remiss of us not to reflect on the lessons learned over the course of building our methods in light of the practical experience of subsequently executing. Our primary learning outcomes are highlighted below:

- **Interviews.** As anticipated, it was a difficult balance to strike with senior leaders between allowing conversations to flow fluidly, extracting depth and keeping conversations on theme. For the large part we consider our efforts to have been successful – but there is no doubt that conversations were far ranging. The resulting transcripts are delightfully rich. However, this made coding more challenging than perhaps would have been the case had we applied a more structured approach to questioning. On reflection we believe that our approach was valuable – but note the amount of effort involved in subsequently transcribing and analysing such a volume of data.
- **Transcriptions.** We consider the nuance of our transcripts to be of critical value – thus we committed to faithfully transcribing discussions. Although we trialled multiple methods from using automated transcriptions through to third

party service provision – we found no adequate substitute for reviewing the transcripts personally and amending errors to accurately reflect language used. The time and effort involved in diligently performing this task was somewhat surprising. That said, we consider the nuanced insights recorded from leaders to be of immense value and we consider ourselves fortunate to have such rare and privileged access.

- **Iteration.** We naively considered the process of planning and conducting research to be a sequential and linear activity. The amount of iteration between our literature review, methods, analysis and execution came as a surprise. However, through each iteration our clarity became sharper and patterns would emerge. Understanding deepened through each iteration.
- **Analysis.** We found the analysis of our data to be the most complex element of our research. The sheer volume of insight available made coding challenging. We noted an early tendency to want to report everything of value – as opposed to focusing on key phenomenon. Our initial account of our results exceeded 25,000 words and had to be materially reduced. At various points in our analysis, we very definitely felt lost but iteration and consultation with both our supervisor and other professors helped to find a path through the complexity.
- **Feedback.** Our feedback workshop (as set out in Chapter 6) provided the opportunity to present our work to leading experts. Presenting four years' worth of work in a ten-minute presentation and providing succinct supporting materials was a cathartic experience – forcing us to focus on the key messages and issues. The resultant feedback was invaluable. We reviewed the recommended changes with a critical eye, noting some and acting on others. We found that the combination of academic insight and practical consideration is powerful and results in improved outcomes.

In conclusion, we have learned a great deal about independent scholarship and research. Whilst one can read about abductive methods and qualitative research – there is much to be learned from the practical experience of conducting the same in the real world.

3.26 Methods Summary

We briefly summarise our methods in Table 11 below, before going on to discuss our findings in Chapter 4.

Reasoning	Abductive study.
Framework	Disciplined imagination - Saetre & Van de Ven (2021).
Research	Semi-structured, qualitative interviews with a purposeful sample of 25 leaders in organisations with revenue in excess $500m per annum.
Interview Method	Constructionist approach utilising Rubin and Rubin's (2016) responsive interview technique.
Interview Format	Remote interviews largely conducted over Microsoft Teams and digitally recorded.
Transcription	Transcripts reported verbatim, using third party organisation to prepare initial transcript, augmented by personal review.
Coding	NVivo used as tool to code results using method advocated by Gioia et al (2012).
Model Validation	Workshop with two of the world's leading advisory firms.

Table 11: Summary of Methods

4.1 Introduction

Our discussions with leaders covered a breadth of subjects related to our core theme – not all of which we can do full justice to here. Table 12 below provides an indication of the frequency with which topics were covered in discussion – highlighting the top 25:

Word	Count	Weighted Percentage (%)	Similar Words
Decision	752	1.46	decision, decisioning, decisions, decisions', decisive
People	740	1.43	people, people'
Data	678	1.31	Data
Automation	437	0.85	automate, automated, automates, automating, automation, automations
Interesting[5]	372	0.72	interest, interested, interesting, interestingly, interests
Human	366	0.71	human, humanity, humanized, humanizing, humans
Company	347	0.67	companies, company
Business	318	0.62	business, businesses, busy
Needs	318	0.62	need, needed, needing, needs
Differently	314	0.61	difference, differences, different, different', differently, differs
Machine	272	0.53	machine, machines
Processing	258	0.50	process, 'process, processed, processes, processing
Case	238	0.46	case, cases
Probably	209	0.40	probabilities, probability, probable, probably
Sense	200	0.39	Sense
Organizations	199	0.39	organism, organization, organizations, organize, organized, organizing

[5] Whilst we recognise that this is not a topic per se – we include as a proxy of engagement in the research area.

Word	Count	Weighted Percentage (%)	Similar Words
Technology	184	0.36	technologies, technology
Team	183	0.35	team, teams
Board	176	0.34	board, boards
Guess	170	0.33	guess, guessing
Systems	170	0.33	system, systemic, systems
Experiments	167	0.32	experience, experiences, experiment, experimenting, experiments
Bias	158	0.31	bias, biased, biases, biasing
Understand	158	0.31	understand, understandable, understanding, understands
Skills	157	0.30	skill, skilled, skilling, skills

Table 12: Word/Subject Frequency

As might reasonably be expected discussions highlighted a range of well reported phenomena – some of which we highlight briefly below for background and context. We then focus the remainder of our results section on those aggregate dimensions that we consider to be most significant to our research question and to extend existing knowledge.

4.2 General Observations

In keeping with Cyert (1963) we note from discussions that organisations 'are made up of hundreds of decision points. That's what businesses are.'[6] They are also highly complex social structures – with the potential to create 'pollution, that skews what is a rational outcome.'[7] The greater the pollution or 'human messiness'[8] the 'greater the probability of things not being done correctly, and decisions being made incorrectly.'[9] Controlling mechanisms have long been established to align individual interests with those of the equity owners and 'to slow thinking down, to stop group think and stop mistakes.'[10] All else being equal then we may reasonably

[6] Service Provider (MoK)
[7] C-suite – Legal (BT)
[8] C-suite – Legal (BT)
[9] C-suite – Partner (MH)
[10] Service Provider (RB)

expect that technology has the potential to assist in the automation of such controlling mechanisms and to support more rational decision making.

We also note in keeping with Edwards et al (2000) and Cyert et al (1956) that organisational decisions exist along a spectrum from the tactical through to the strategic. At the tactical end of the spectrum are 'episodic, repeated decisions'[11] whilst at the other extreme are 'big decisions like "do I buy this company?"'[12] We find strong support to suggest that automation of decision making is gradually moving from left to right along this spectrum. At the tactical level automation results in 'a binary replacement'[13] – although we note that such resources are often redeployed. At the further extreme there is universal expectation from the leaders we spoke to that data will increasingly underpin strategic decisions and will augment and supplement human expertise.

It is apparent that the scale and ambition of adoption of automated decision making within organisations varies materially from both an industry and functional lens. Whilst the 'world is changing so quickly'[14] and 'every single industry, you can't name one that isn't thinking about digital and the impact it's having on the sector and their business'[15] - the pace of change is not equally distributed. 'What we see is the intensity or maybe the investment change depending on industry.'[16] Advisory firms and service providers have long since organised themselves around industry sectors and functional competency areas in order to be able to bring economies of scope to their clients and to deepen their understanding of client challenges. This approach seemingly pays dividends in relation to automation – 'that's how we see the opportunity map. So, industry lens and functional lens.'[17]

4.3 Aggregate Dimensions

We have focused our results on three aggregate dimensions that relate back to the open questions we observed at the conclusion of our literature review. Firstly, we find that data is increasing exponentially, and that this explosion of data is fuelling automation of decision making. Progressive organisations deploy impartial, perfectly adapted machines as effective coping mechanisms in response, with multiple drivers impacting the pace and scale of adoption.

[11] Service Provider (MoK)
[12] Service Provider (MoK)
[13] C-suite – Legal (BT)
[14] Advisory (CV)
[15] Board Member (RF)
[16] Service Provider (FL)
[17] Advisory (TM)

Secondly, we find that judgement and experience continue to be valued by organisations in relation to high-stakes decisions involving human interaction and the need to project the future - creating engineering bottlenecks. Finally, we find that customers, regulators and professional bodies are increasingly both accommodating and resisting automation – with trust and explainability impacting deployment. We find that a conservative approach is being taken to black-box techniques by the majority of organisations. As such we find that Pickering's (1993) mangle is increasingly impacted by factors external to the organisation.

We recount these results below before discussing the implications in subsequent sections of this paper.

4.4 Data Fuels Automation of Decision Making

4.4.1 Aggregate Dimension

Data fuels the automation of decision making.

4.4.2 Synopsis

The volume and type of data is increasing exponentially. Machines are perfectly adapted to process and drive insight from huge data sets (unstructured, semi-structured and structured) that would be beyond the cognitive ability and temporal capacity of human agents. Machines do not tire, act with perfect impartiality and have become increasingly accessible as the cost of technology has reduced. As such, machines are increasingly becoming effective coping mechanisms for organisations – reducing cost, releasing capacity, increasing data transparency, and eliminating bias. Additionally, such machines may pioneer new insights that would be indiscernible or impracticable for human agents.

4.4.3 Data Volume and Type – Structured, Semi-Structured and Unstructured Increasing Rapidly Leading to New Opportunities to Exploit

Data is becoming almost synonymous with technology in the minds of business leaders – with one CEO going as far as to state:

> "The data industry has just burgeoned and is similar to the early days of oil. I quite often say that it's a lot like oil because it's coming out of the ground raw. It's not of use to anybody – but once it's been processed it can be incredibly valuable." C-suite – CEO (RH)

The analogy is apt given that recent advances in technology have led to significantly reduced costs for collecting and storing data,[18] whilst in parallel creating new data sources and affording organisations the opportunity to create 'new forms of value.'[19] Data comes in a variety of forms and technology is providing the enabler to look at both structured, semi-structured and unstructured data with an increased sense of purpose – whilst itself creating new forms of data as a by-product of increasingly digital operations.[20]

One of the key themes to emerge across our discussions was a clear sense that organisational decisions will be increasingly data driven – with extensive evidence of businesses investing

[18] C-suite – CIO (GC)
[19] C-suite – CEO (RH)
[20] See Chapter 6 for note of caution regarding the use and appropriateness of this analogy.

heavily in associated capabilities across the leaders we spoke to. Whether ‘fixing their data strategy’[21], recognising the importance of ‘good information and good insights to make decisions’[22] or simply an acknowledgement that the ‘best decisions are made based on information and data’[23] – there is increasing focus on this subject. This was perhaps most aptly summarised by one board member who commented that:

> “The second direction which I can see happening as well, is around data that you mentioned and if not more data at the board level, the expectation that the executive is getting more data of better quality on which to base those decisions. And, you know, all companies are now so rich with data and most importantly, the quality of that data is much more reliable. So that, you know, in terms of historical trends or market shares, or detailed customer analytics and CRM systems which have come on leaps and bounds. The ability to slice and dice one's data, differentiate ones' customers, and be very specific in targeting customers using elaborate data segmentation - that is all moving at a pace and a lot of boards have got a lot more digital specialists on the board because every single industry, you can't name one that isn't thinking about digital and the impact it's having on the sector and their business.” Board Member (RF)

This direction from the top is shared amongst the C-suite executives we spoke to and supported by both advisory firms and service providers. Whilst industries, sectors and individuals are divided on the extent to which such focus will result in displacement versus augmentation – the expectation that data will play a prominent role in decision making is universally supported in our results.

We find evidence that the amount and type of data that is available is growing exponentially. In certain instances, data is simply being converted from traditional format to digital. For example, pharmacovigilance[24] was highlighted as a use case where historically doctors recorded adverse reactions to drugs by hand – scratching their findings on the back of pieces of paper. These insights would then be read and submitted, by expensive and experienced pharmaceutical professionals. However, ‘by converting handwriting into text – you can create a data input

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[21] Advisory (TM)
[22] Board Member (AH)
[23] Board Member (HB)
[24] C-suite – CEO (RH)

where there wasn't one before.'[25] In other words, not all data is new – but the digital nature of new formats creates opportunities to exploit. The same is true of law firms who hold significant amounts of data on contract terms[26], or banks that hold valuable data about consumer habits and trends.[27]

In addition, technology is creating entirely new sources of data – both structured and unstructured. The trend towards wearable devices provides a significant amount of data about habits and health.[28] The volume of smart sensors *in-the-world* has increased exponentially in recent years – be that from consumer phones exploited by the navigational platform Waze[29] or connected devices deployed with intent around a specific business outcome.[30] Thames Water serves as a great example as highlighted by one Service Provider:

> "Thames Water had the same thing and were getting fined for leaks, water leaks and receiving quite big regulatory fines as a result. And they were like, "we need to put a stop to this." So, again, the solution was an automation solution - typically how they were doing it was you had all these engineers who would get information from all these water pipes with pressure sensors and things like that on them." Service Provider (KR)

These devices provide passive data to organisations which can then be interpreted by intelligent agents. As highlighted, this data in raw format has limited value – but when converted to 'extract insights'[31] - can be exploited to support decision making. Additionally, we find support that a combination of structured, semi-structured and unstructured data will provide greater holistic insight to leaders.[32]

One C-suite executive highlighted that banks are beginning to monetise their data by providing insight to external organisations to support decision making. Understanding consumer spending patterns for example can help to determine the location of retail outlets.[33] In the media space organisations are using data insights to drive creative decisions.[34] The massive amount of public

[25] Advisory (SC)
[26] C-suite – Legal (BT)
[27] C-suite – Risk (CO)
[28] C-suite – CIO (GC)
[29] C-suite – Strategy – (BM)
[30] Service Provider (MoK)
[31] C-suite – Legal (BT)
[32] Service Provider (AL), Service Provider (FL), CEO (RH), Advisory (TM)
[33] C-suite – Risk (CO)
[34] C-suite – CIO (SB)

data on social media sites provides a huge data source to determine features and content that is landing well with consumers, or analogous trends than can serve as lead indicators of likely interest areas:

> "There was a time, when the editors were king, and they'd decide, 'I feel like writing a story on that.' Not anymore because now we are calculating the return on investment on every story. Now we're saying 'you wrote this story, this is how much value your story generated. Between all of the components we have – whether it's ad driven, subscription or commerce." C-suite – CIO (SB)

As such the vast majority of leaders we spoke to are either beginning to understand the value of their existing data or are already down the path of exploiting.

We found strong evidence that adoption curves differ by industry and function. One advisory partner articulated a simple framework through which to consider data driven decision making against that backdrop. At the 'top of the adoption curve are organisations that typically have large quantities of semi-structured or well-structured data.'[35] Banks serve as a good example of this where they hold data on 'millions of credit holders'[36] and as such automation of credit strategies is the only way to 'cope with the scale, size and complexity.'[37] Then there are organisations where data sets are less large and less well structured – but where use of analytics can help to solve 'high-cost problems.'[38] This category includes mining and processing industries where data and analytics can be used to solve for issues such as defect detection. Finally, we have the 'laggards.'[39] Such organisations either lack data entirely or existing data is unconsolidated. This category includes airlines. Whilst this may seem counterintuitive, the suggestion is that the data required to solve complex aviation problems is spread thinly across the supply chain from engine manufacturers through to operators.

4.4.4 Machines as Effective Coping Mechanisms in Response to Exponential Growth in Data

We found strong recognition that the volume and complexity of data sets is becoming increasingly challenging for human agents.[40] This complexity is felt throughout organisations

[35] Advisory (TM)
[36] C-suite – Risk (CO)
[37] C-suite – Risk (CO)
[38] Advisory (TM)
[39] Advisory (TM)
[40] C-suite – Risk (CO), C-suite – CFO (AS), C-suite – CEO (RH), Service Provider (AL), Board Member (HB), C-suite – Legal (BT), C-suite – CIO (GC), Service Provider (MoK), Service Provider (RB), C-suite – CIO (SB)

with one board member commenting that the amount of information provided to support decisions was ‘overwhelming’:

> “Every request I told you about, in reality, is twenty to thirty pages. We approve twenty or thirty every couple of weeks. Frankly speaking, after some time, you just end up looking at the summary and treat the next thirty pages as appendix.” Board Member (HB)

If the provision of investment support data is considered challenging given cognitive limitations and time constraints, this pales in comparison with data sets involved in medical diagnosis[41], legal e-discovery[42] and the Serious Fraud Office where:

> “They look through approximately 2 to 3 billion documents a year. Which if you print it out on paper, is a pile from here to near orbit. So, if you think that 300 investigators are going to read through a pile of paper that’s 40 kilometres high, you are clearly smoking something.” Service Provider (FL)

Unsurprisingly the larger the data set the more challenging unaided human driven insight becomes – not just because of cognitive limitation, but because of time.[43] Leaders acknowledge that ‘human brainpower is relatively limited as it relates to looking at data in depth, breadth and speed.’[44]

A particularly insightful comment was made by one CEO who stated that ‘data comes in different formats and the current generation of company leaders work primarily on structured data.’[45] This was reinforced in a subsequent discussion where it was suggested that data historically was limited and could be easily visualised within ‘one bar chart.’[46] However, given the data sources we have already highlighted and the volume that is anticipated in the future - machines will likely be required to make sense of this vast array of data and provide insights. Machine learning will increasingly help to augment the insights derived[47] - with natural language processing driving exponential volume of data in the near future.[48]

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[41] C-suite – CEO (RH)
[42] C-suite – Legal (BT)
[43] C-suite – CEO (RH)
[44] Service Provider (FL)
[45] C-suite – CEO (RH)
[46] C-suite – CIO (SB)
[47] C-suite – CEO (RH)
[48] C-suite – CIO (SB)

Where sufficient, good quality data is available machines appear perfectly adapted to process such data to make superior decisions. Putting aside the issue of whether machines augment or displace human agents, we found strong evidence that leaders recognise the superior power of machines to process large volumes of data:

> "Here we think of things like mining and processing industries where analytics can be used to drive improvement in throughput – also in manufacturing industries, particularly heavy manufacturing around use cases like defect detection for example – like sheet metal – where complicated machine vision algorithms allow you to detect hairline weaknesses in product that you wouldn't otherwise be able to detect." Advisory (TM)

Similar use cases were highlighted in pharmaceutical[49], utilities[50], media[51], banking[52] and health care.[53] As one CEO highlighted 'software doesn't get tired. It's able to recognise patterns at a much faster rate than a human can.'[54] Thus, machines provide the opportunity to drive insight that would be neither practicable nor economically viable for human agents. As such we may start to consider machines as effective coping mechanisms for organisations.[55] In high volume businesses automation can be considered as necessary to 'cope with the scale and complexity'[56] of the organisation. Several use cases were highlighted in discussion from anti-money laundering[57] through to avoiding regulatory fines for water leaks.[58]

Machines act with indifference. On the assumption that data is provided in an unbiased manner – machines will act will perfect impartiality as 'AIs aren't biased in any way shape or form.'[59] This impartiality leads to use cases supporting activity which historically has been heavily associated with human bias – including screening of CVs[60], credit assessment[61] and even health and safety assessments.[62] This lack of bias also enables machines to improve over time through

[49] C-suite – CEO (RH)
[50] Service Provider (KR)
[51] C-suite – CIO (SB)
[52] C-suite – Risk (CO), C-suite – CIO (GC)
[53] C-suite – CEO (RH)
[54] C-suite – CEO (RH)
[55] C-suite – Risk (CO)
[56] C-suite – Risk (CO)
[57] Service Provider (KR)
[58] Service Provider (RK)
[59] Service Provider (MoK)
[60] C-suite – HR (JC)
[61] C-suite – Risk (CO)
[62] Service Provider (MoK)

machine learning. Again, unlike human agents this learning will be formulaic in nature and built over vast data sets. As commented by one CIO, 'machine learning is really powerful because it's all about the power of repetition and more and more data.'[63]

Technology has the potential to increase transparency by providing real-time access to data which would historically have been inaccessible to many. This is referred to by some as 'democratising data.'[64] Data democratisation enables organisations to take data that would previously have sat in the hands of a relatively small number of resources and 'put it on everyone's iPhone.'[65] This is potentially appealing to board members in providing the 'right data in a proper way – because I think this would help the board member to do his own duties in the right way.'[66] In practical terms this enables organisations to share information broadly and to use technology to provide insight that would previously have been accessible only via specialists 'so basically you've got your ten most experienced colleagues on your laptop.'[67] Internally this is incredibly powerful – although with external data sets it potentially results in certain expertise becoming akin to a 'commodity.'[68] As one COO remarked – this can make it challenging to differentiate 'because everyone's got the same data sets and the same AI.'[69]

4.4.5 Narrow Use Cases Resulting in Proliferation of Pilots

Notwithstanding the foregoing, what was clear from discussion with business leaders, and in particular Service Providers and Advisory firms is that the vast majority of automation use cases are against narrow contexts.[70] As one partner noted 'we have seen massive uptake on simple technologies like RPA. It is hugely rules based. But how many organisations are really leveraging AI in a meaningful way at the moment. Not many.'[71] This myriad of spot solutions is challenging for organisations and an inhibitor to organisational adoption.

The discussion of general AI or general intelligence was raised by several partners[72], with one CEO stating:

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[63] C-suite – CIO (GC)
[64] C-suite – Strategy (BM)
[65] C-suite – Strategy (BM)
[66] Board Member (HB)
[67] Advisory (SC)
[68] C-suite – Legal (BT)
[69] C-suite – COO (DH)
[70] Service Provider (FL)
[71] Advisory (CV)
[72] C-suite – CEO (RH), Service Provider (FL), C-suite – Risk (CO)

> "I'm giving a talk the week after next on the difference between Singular AI and General AI. The reality is that we're still a very long way away from General AI. If you, however, think about AI as a tool to actually tackle specific problems, which humans actually aren't really that good at, it's probably a better way to think about how or what type of technology will change the business horizon over the next five years. In parallel with that, there's a second stream - which is you've got to look at the work that people like deep mind are doing towards general AI, and they've made some incredible breakthroughs in the last couple of years. But they are still a long way away from being able to create an intelligence which can adapt to multiple scenarios. And therein lies the difference between Singular AI and General AI." C-suite – CEO (RH)

The same CEO went on to narrate an account of how they had recently taught their grandchild to throw a table tennis ball and have it spin backwards towards them. Shortly afterwards the same child was in the garden – picked up a football and applied the same principle without prompting. The child was able to take the principle that they had learned indoors, with a small ball and a hard surface and apply the same principles in an entirely different context. The ability to move seamlessly between contexts - is the nirvana of data science. However, as the Global Lead of Data Science & Machine Learning at one of the world's largest Service Providers noted 'we're so far away from that, that I'm not sure we're going to see that in our lifetimes.'[73]

Whilst it was acknowledged that General AI is not a precondition to being able to extract value from automation and that organisations can still derive 'enormous advantage out of the real difference between a human and an AI singular device'[74] – it is not without challenges. Service Providers highlighted that singular use cases were resulting in 'pilot purgatory.'[75] The fact that automation cannot span beyond specific use cases results in situations where a single organisation can have '1200 AI use cases – 1200! Jesus Christ, that's a lot of use cases.'[76] Another partner highlighted the same issue 'where you walk around the business and you'll end up with hundreds of use cases for AI.'[77] The challenge then is obvious – 'if it took me two years to build the first use case, how am I going to build 500 more?'[78] This then becomes a major

[73] Service Provider (FL)
[74] C-suite – CEO (RH)
[75] Advisory (TM)
[76] Service Provider (FL)
[77] Service Provider (MoK)
[78] Service Provider (MoK)

inhibitor to automated solutions in the near term and 'the mistake the wider world thinks about when they hear AI or machine learning is they don't know how narrow the effectiveness of that particular algorithm is in terms of domain.'[79]

[79] Service Provider (RB)

4.5 Judgement and Experience Highly Prized in High-stakes Decisions

4.5.1 Aggregate Dimension

Human judgement and experience continues to be valued in relation to high-stakes decisions requiring human interaction and/or projections of the future.

4.5.2 Synopsis

Human judgement and experience continue to be valued by organisations in the absence of perfect data and express acknowledgement that data alone is insufficient to fully inform certain decisions. Judgement is an intangible mix of traits that is difficult to adequately define and thus automate. Judgement is particularly valued in relation to human-to-human interactions and high-stakes decision making which involve predicting or anticipating the future. Paradoxically it is precisely because judgment is subjective and intangible that makes it both prone to error and bias and yet equally the element that makes it most valuable in achieving exponential business outcomes.

4.5.3 Judgement is an Intangible Mix of Skills and Traits Making it Hard to Automate

We have commented previously that data fuels automation. However, leaders seemingly recognise that there are instances where data is insufficient to inform decisions resulting in 'grey zone decision making'[80] calling for human judgement and experience. These traits are highly prized amongst elite professionals across a broad range of industries where 'there's a lot of power that rests in the expert.'[81] Where situations call for something other than binary, data driven, rational decisions – judgement is required to select between alternatives. Such judgements call for the ability to assimilate structured, semi-structured and unstructured data simultaneously – taking account of industry, context, human factors, past data and often requires some degree of projection. As one board member noted – judgement is an 'intangible mix.'[82] Various phrases or traits were highlighted during discussions including 'intuition'[83],

[80] C-suite – CFO (DC)
[81] C-suite – Legal (BT)
[82] Board Member (AH)
[83] Board Member (AH), C-suite – CFO (AS), C-suite – Strategy (BM), Service Provider (RB), C-suite – Legal (BT), C-suite – CEO (RH)

‘gut’[84], ‘creativity’[85], ‘IQ and EQ’[86], ‘common-sense’[87] and ‘wisdom.’[88] In the vast majority of discussions experience was talked about as being a critical part of judgement – ‘having seen things before is helpful.’[89] Ideally experience should be coupled with information – with one leader describing judgement as a ‘marriage of data, analytical skills and experience.’[90]

In turn, we can think of experience as the accumulated understanding of ‘how things work, how people work, just being knowledgeable about life.’[91] Experience is accumulated over time and is difficult to short-cut – ‘part of that is just getting older and appreciating the subtleties of life a lot more.’[92] It is a trait that is prized at all levels including at the board where one board member reflected that ‘better decisions are made by people who have experience not just of the world but also the particular environment in which they’re operating.’[93] The latter part of this statement is interesting given that experience can range across a spectrum - from very narrow, vertical experience to incredible breadth. Both are prized by organisations and professions but in different circumstances. The narrower the context – the greater the degree of specialist experience required to support. A specialist litigation lawyer for example would likely serve as a poor divorce practitioner.[94] In such instances experts are valued ‘for the quality of advice on tricky questions.’[95]

The ability to scale experience across contexts is arguably a uniquely human trait and again valuable to organisations. Professionals lacking experience of a certain situation may be able to draw upon analogous situations to drive insight – ‘can we see something that looks or smells like what we’re trying to do so that we could potentially learn from it.’[96] As one CFO noted, experience enables human agents to contextualise challenges and to build competence over time - learning ‘all the tricks of resourcefulness and cunning and how we are going to do this.’[97]

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[84] Board Member (AH), C-suite – CFO (AS), C-suite – Legal (BT)
[85] Board Member (AH)
[86] Board Advisor (SR)
[87] C-suite – CFO (AS), Board Advisor (SR), C-suite – CFO (BF)
[88] Board Advisor (SR)
[89] Service Provider (RB)
[90] C-suite – Strategy (BM)
[91] Board Member (AH)
[92] C-suite – COO (DH)
[93] Board Member (RF)
[94] C-suite – Legal (BT)
[95] C-suite – Legal (BT)
[96] C-suite – CFO (AS)
[97] C-suite – CFO (BF)

In the absence of perfect data – real world decisions involve shades of grey – or as one COO commented 'practically every decision I think now is in degrees.'[98] As an example – one board member recounted a recent transaction where they had been responsible for disposing of certain high value assets:

> "The chairman of the board told me, "$2 billion is great, don't be greedy," but I pushed and I got to $2.15 billion. I felt if I wanted another fifty, I could have, but we reached the level where we were concerned. So, this deal is linked to casinos and casinos in Vegas are linked to tourism and the restrictions in hotels. We were at that stage - June time - so we knew the 4th of July was coming. The Americans, had covid cases going down but we knew there would be a time where it would start going up." Board Member (HB)

The judgement as to where to close this particular transaction involved a range of $200m USD. Thus, judgement results in tangible business outcomes and is of value to shareholders. It was also highlighted that good judgement is not just about making the right decisions but equally knowing the right questions to ask[99] - 'in business school you're taught to give the right answer. In law school you're taught to ask the right question.'[100]

4.5.4 The Future is Difficult to Predict, Hard to Reduce to Data and Necessary to Support Most Complex Organisational Decisions

One very experienced board member commented 'we all know the most complex business decisions are very large capital allocation decisions – should we invest, or do we not invest?'[101] This statement was borne out by other conversational partners.[102] What seemingly makes these decisions complex is the fact that they involve no small degree of 'trying to predict what the future is going to look like.'[103] All of the historic data in the world is not going to determine with certainty how the future will play out and as such 'predicting the future is always – I would say an art – it can't be done in a scientific way.'[104] This is made even more challenging by the fact that 'there's so much flux in the world at the moment.'[105] Two years ago for example no

[98] C-suite – COO (DH)
[99] C-suite – Partner (MH), C-suite – Law (BT), C-suite – CIO (GC)
[100] C-suite – Legal (BT)
[101] Board Member (RF)
[102] C-suite – CFO (AS), C-suite – CFO (BF), C-suite – COO (DH), Board Member (AH), Board Member (HB)
[103] Board Member (AH)
[104] Board Member (HB)
[105] Advisory (CV)

one could have imagined the pandemic that we are currently living through and its existential impact on organisational outcomes. Yet many business decisions require that leaders anticipate the future. The ability to do so effectively can result in differentiated business outcomes.

We might usefully delineate here between the creative process of imagining potential futures[106] in the broadest sense and the narrower forecasts required by the majority of business decisions. In the former instance:

> "I think certain people have good imagination. My father was an artist, right? So, he lived in his inner world in a way. He had a very vivid imagination. Part of having a good imagination helps you think about possibilities. Think about what could be rather than what is. I think that's been a big help to me, to actually be able to sort of think about the future. What could the future look like? What are the possibilities?" Board Member (AH)

The ability to imagine future possibilities is a key attribute of certain visionary leaders. Steve Jobs[107] was highlighted as a ready example of someone who was able to reimagine the future – 'one of the very first slogans at Apple was 'think different.''[108] For those with creative vision the ability to imagine possibilities is a key differentiator and enabler – whilst for those organisations that are unable to project forward – such limitations will likely be an inhibitor to long term growth. 'Lack of ability to see the future means that you don't embrace what is very simple, tried and tested technology.'[109]

4.5.5 Human to Human Interactions Require Soft Skills and is Challenging to Automate

Through discussion with leaders, it also became apparent that judgement often ties back to people. For leaders, the ability to read, manage and motivate people is critical and as noted by one board member – 'all judgements around people are soft.'[110] Whether it is how to get the best out of employees, to recruit new talent or as one leader so eloquently observed to 'know when someone is bull-shitting me'[111] – judgement is critical to success in the complex social constructs that constitute large businesses. This was perhaps most neatly summarised by one corporate coach with decades of experience in mentoring senior leaders, who observed that

[106] Board Member (AH), C-suite (GC)
[107] C-suite – CEO (RH), Advisory (SC)
[108] C-suite – CEO (RH)
[109] Advisory (SC)
[110] Board Member (RF)
[111] Board Member (AH)

judgement might best be described as a mix between EQ, IQ and common-sense. 'You get people with IQ and common-sense and with that combination they can do quite a lot.'[112] This notion of common-sense recurred throughout discussions and much like judgement and experience - was prized by leaders.[113]

We also noted that human to human interactions are extremely challenging to automate. One advisory partner described a piece of automation software that enables their client to build automated proposals for prospective clients. The software is capable of automating 80-90% of the proposal – so removing a significant amount of previously manual activity. However, such solutions 'can't yet take the requirements, it can't yet have the conversation and it can't close the deal.'[114] We commented previously on divorce lawyers and the case in point is perfectly illustrated by the following account:

> "Divorces are messy. They're rooted in deep-seated anger, and betrayal, and all kinds of crap that has nothing to do with the money. And you could have a rational, you know, well split the difference, or offer her 2000 more, and let's be done with it. And people say, "Are you nuts? I'm not offering that bitch a dime." You know, and they'd rather burn the whole house down. And that's where the human, a good human divorce lawyer can take some of the heat out of that, take them for a drink and say, "Listen, I hear you. She's a bitch. But, you know, in the end, think about your kids. I've seen people die of cancer because they got so stressed." And you know, and you can have those conversations and try and relate on a human to a human level where emotions - the law is a place where emotions get really jumbled." C-suite – Legal (BT)

Thus, whilst we may think of law as a technical discipline it is actually far softer in many ways – 'because if you think about what the law really is, it's humans organising things for humans.'[115]

In parallel, whilst banks are increasingly looking to automate transactional relationships – such as those historically associated with branches – high-stakes relationships remain critical. Relationship managers within investing banking are highly sought after given that 'there are very few people who have those relationships and if you want to hire them, you have to pay a

[112] Board Advisor (SR)
[113] C-suite – CFO (AS), Board Advisor (SR), C-suite – CFO (BF)
[114] Advisory (SC)
[115] C-suite – Legal (BT)

significant premium.'[116] Whilst a bank's logo and brand plays a role – clearly relationships are valued at the elite levels of both organisations and in the eyes of high net-worth individuals. These relationships may prove to be one of the final engineering bottlenecks to be overcome as highlighted by one CIO:

> "But they are actually, in many cases grounded in a series of essential truths, particularly when they're people-to-people interactions, or people dealing with people or treating people in its broader sense whether it's educating them or curing them, or engaging with them. Those factors are really quite relevant, and are actually much more important as a skillset than is obvious to the layperson or someone who doesn't do that as a profession. Therefore, if you're an engineer, and you have to codify that, it's actually really quite a hard thing to do." C-suite – CIO (GC)

That said, the number of domains within which these relationships continue to exist will likely reduce with automation – leaving the remaining jobs in the hands of the elite.

4.5.6 Engineering Bottlenecks and a Cautionary Note

From discussion with organisational leaders, words such as 'gut'[117] and 'intuition'[118] were used repeatedly to describe human decision making. The challenge for those looking to model human behaviour is that this intuitive or gut instinct is 'murky'[119] and thus hard to explain and encapsulate through process. Unlike the standards applied to machines, human intuition is actually celebrated in certain instances despite an agent's ability to reduce their decisioning to reasoned explanation:

> "But it's, there's something in someone who has done something for 30 years, whatever that thing is, that they might not be able to fully explain themselves, but that is valuable. I was reading the other day about a forgery; it was a great Greek Roman statue that was unearthed and the Metropolitan Museum of Art was trying to decide whether to buy it. And if it was genuine, it was one of the most priceless discoveries in modern history in terms of its intactness and beauty. And all these experts had considered it in a very studied way. A lot of

[116] C-suite – Risk (CO)
[117] Advisory (TM), Board Member (AH), C-suite – Legal (BT), C-suite – Strategy (BM), Service Provider (RB)
[118] Service Provider (RB), Advisory (SC), Board Member (AH), C-suite – CFO (AS)
[119] C-suite – Legal (BT)

> facts and concluded it was accurate - it was genuine. And then one of the most experienced art experts in the world was invited to come and look at it, and he said later, he described it as, just the second, he saw it, there was something about it that was off. He couldn't explain what it was. But something in his gut told him that, "That's fake." "It's just not real." And it was that intuition that sort of led him to do a whole bunch of other things that ultimately proved that it wasn't real – it was fake." C-suite – Legal (BT)

Human intuition may then be considered the oldest form of black-box – impenetrable and mysterious. Not all decision inputs and processes can be easily rationalised – even in areas we may consider to be highly numeric. One board member highlighted for example that in relation to mergers and acquisitions – 'the third that are successful are only successful for reasons you never put in your model.'[120] The same point was reinforced by a Pharmaceutical CFO who highlighted that even with the most precise forecast models 'most of the time you are going to be precisely wrong.'[121]

Thus, it is important to add a cautionary note. Despite judgement being highly prized, leaders also recognised that 'bias exists everywhere'[122]. This creates something of a paradox. On the one hand experience is highly prized, on the other hand, bias is seen as destructive. Yet outside of nomenclature, we question the tangible difference between bias and experience? Bias in certain contexts could equally be labelled as experience. A leader experiences certain phenomenon in the past and expects such trends to continue into the future when assessing a decision. Is that bias? Or is that experience? Is it valuable and to be encouraged and nurtured? Or destructive and to be eliminated? It seems in a significant number of instances that bias is actually a 'societal norm.'[123] Thus we need to be careful to delineate. Clearly removing bias from things like recruitment decisions is a desirable outcome.[124] However, if data suggests over time that a certain demographic achieves the best results once in post –we would be poorly advised to artificially diversify such teams for the sake of meeting a societal expectation.

Despite, the fact that experience and judgement are prized as traits in effective leaders, there was equally acknowledgement that such judgements are often erroneous. As one CFO commented on the acquisitions they had been involved in - 'when I look back at all the deals

[120] Board Member (RF)
[121] C-suite – CFO (AS)
[122] Service Provider (RP)
[123] Service Provider (RP)
[124] C-suite – HR (JC), C-suite – Strategy (BM), Service Provider (RP)

that I've ever built – I've been wrong on every single one of them, whether for the good or the bad.'[125] Part of this experience contributes to growth and learning – but equally for leaders entrusted with stakeholder funds this seems, on the face of, it a surprising admission. Another CFO described a situation where a particular leader wished to build a casino in Edinburgh – despite the fact that 'there was no evidence in my mind that it would stand a fourth – and arguably three is going to become two rather than four.'[126] They went on to note that the decision was irrational from a shareholder perspective – but highly rational from the perspective of that individual in anticipating headlines along the lines of 'hometown girl brings casino to Edinburgh.'[127] In such instances we may consider certain enabling functions in organisations to represent machine intelligence.'[128] In other words such functions and leaders are there to impose rationality and to try and eliminate bias. A point reflected on by another CFO who stated:

> "So, for me, making data-based decisions is probably as, if not more important, than the relationship component. I'd like to think that I'm unbiased or not necessarily influenced by relationships, but we all know that that is often the case. We're humans after all." C-suite – CFO (AS)

Relationship bias is then a further reason to caution against over confidence in human decision making.

It is the lack of perfect data that seemingly justifies the use of intuition – even in high-stakes decision making scenarios. As one COO noted 'no one has perfect information. No one has perfect experience'[129] and thus human agents augment this data with softer decisioning skills in relation to 'grey areas.'[130] This 'subjectivity'[131] or 'ambiguity'[132] is exaggerated by interaction with other human beings and the fact that the world 'isn't always logical.'[133] A myriad of diverse examples were given of intuitive decision making, including, lawyers advising emotional divorcees[134], doctors diagnosing patients[135] and leaders making investment

[125] C-suite – CFO (AS)
[126] C-suite – CFO (BF)
[127] C-suite – CFO (BF)
[128] Board Advisor (SR)
[129] C-suite – COO (DH)
[130] Service Provider (MoK)
[131] C-suite – Strategy (BM), C-suite – Risk (CO), C-suite – COO (DH)
[132] C-suite – CIO (GC)
[133] C-suite – Legal (BT)
[134] C-suite – Legal (BT)
[135] C-suite – CIO (GC)

decisions.[136] Seemingly the higher the stakes the greater the chance that subjectivity, intuition and gut feel comes into play – suggesting a potential engineering bottleneck for machines:

> "So, there's a sort of some sort of correlation probably between the ambiguity of the target, the outcome, and the ambiguity of how that process happens to be performed - which dictates how long it will be before the AI becomes a dominant factor in that work." C-suite – CIO (GC)

However, this seeming acknowledgement and acceptance is somewhat challenging.

One of the interesting observations to come out through discussion was the notion of judgement as an organisational competitive advantage. In a world where data is increasingly democratised one advisory partner observed:

> "I think that's an interesting place that we haven't got to yet. But I think that's where we're heading. Its competitive advantage will lie in either, in data that's not generally available. And the places where human judgment is required to assess an information set that cannot be digitized." Advisory (SC)

In other words, in a likely future where automation has levelled the playing field in so many ways and limited the number of instances where human decision making is applied – its impact may be exponentially significant. This theme was seconded in a subsequent discussion:

> "Sorry, there any number of points there. One is the... everyone starts to think the same because everyone's got the same data sets and the same AI. Therefore, you get to orthodoxy very, very quickly. Therefore, it's very hard to differentiate. It could be one outcome from that. There's another outcome, I think, which is... if you could possibly differentiate - and by the way, I believe long-term differentiation is about culture, although machines may remove culture, that long-term differentiation I think is about culture. I don't think machines can create culture. That's just the way it is." C-suite – COO (DH)

Further colour to this observation was added by a CEO who again referenced Steve Jobs as an example of the type of differentiation afforded by elite judgement enabling 'seismic change and seismic shifts.'[137] Thus, the more critical and strategic the decision – seemingly, the greater the emphasis on human judgement.

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[136] C-suite – CFO (AS), Board Member (RF), C-suite – CEO (RH), C-suite – CFO (BF)
[137] C-suite – CEO (RH)

4.6 The Nature and Form of Accommodation and Resistance to Automation is Evolving

4.6.1 Aggregate Dimension

The nature and form of accommodation and resistance to automation is evolving.

4.6.2 Synopsis

The adoption of automated decisioning solutions is advancing rapidly across a range of industries and functions driven by compelling business drivers. The ability to reduce costs, increase capacity, pioneer new ways of monetising data and to address complexity results in automation becoming an increasingly existential capability. Where automation displaces human agents limited resistance can be proffered. Resistance looks set to increasingly come from outside organisational boundaries in the form of customers, regulators, professional bodies, and governments.

4.6.3 A Broad Range of Adoption Drivers are Accelerating Automation

Through our discussions with leaders, it became very apparent that automation is accelerating across industry and function driven by a raft of compelling adoption drivers. Unsurprisingly, the means to reduce cost was identified as a primary theme and driver.[138] For digital natives, technology is enshrined from inception, disrupting traditional organisations and forcing them to look to automation to compete in situations where 'traditional business levers have less and less of an impact.'[139] Amazon Go serves as a good example of disruptive innovation that has taken automation to new levels – removing the need to check out and eliminating manual payment. The ultimate in convenience experience – literally grab and go – with the unsavoury process of actually paying for items being fully automated. The automation of the physical experience in store allows data to flow seamlessly through systems reducing the need for human agent touch points in terms of inventory, stock ordering and accounting:

> "So, you take a retail. For example, you take Amazon's - I don't know what they call them - but their stores with no colleagues in. Literally, we're checking out ourselves as a customer, that transaction is picked up by point of sale, it flows through the ERP, it flows through an automated financial close - it ends

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[138] Advisory (CV), Advisory (SC), Advisory (TM), C-suite – CFO (AS), C-suite – Risk (CO), C-suite – CFO (DC), C-suite – CIO (SB), Service Provider (AL), Service Provider (KR), Service Provider (MoK)

[139] Advisory (TM)

up in your financial numbers. In theory, there's very little human intervention in that process at all." Advisory Partner (CV)

Addressing a use case from scratch with modern technology enables forward thinking organisations to completely reimagine a traditional experience and automate significant elements of the end-to-end processes – leaving traditional organisations scrambling to catch up.

However, not all companies are in the position to start from scratch and reimagine their business model. In response CFOs[140] highlighted that benchmarking internal costs as a percentage of revenue was a key driver in looking towards automated solutions – starting with their own functions. This was a point reinforced by one advisory partner who highlighted that the trend was increasing at pace and that 'best practice is something like half a percent of revenue on a cross-industry basis, from 2% yesterday.'[141] This trend was also seen in banking where 'executives don't like to admit it, but it is a cost reduction strategy'[142] and in media where 'the fundamental driver I think is profitability.'[143] This reinforces what we already know – that technology has the ability to drive efficiency through process redesign and to eliminate manual work previously performed by high cost human agents. With margins declining in many industries through competitive pressures and challenges growing the top line[144] there is a strong compulsion for organisational leaders to leverage automation to redress.

That said capacity is increasingly important for organisations[145], with efficiency gains in many organisations not automatically being used to eliminate heads – 'this isn't about stripping out thousands and thousands of jobs. This is about creating headroom in your organisation.'[146] This capacity enables organisations to absorb new work with zero incremental cost – and to avoid competing for talent in highly competitive labour markets. It also enables organisations to provide greater opportunities to their existing talent to do meaningful work by automating mundane, repetitive tasks.[147] As one service provider commented, this affords organisations the opportunity to deploy capacity in areas that represent the 'highest and best use of their

140 C-suite – CFO (AS), C-suite – CFO (DC)
141 Advisory (CV)
142 C-suite – Risk (CO)
143 C-suite – CIO (SB)
144 Service Provider (KR)
145 Advisory (SC), C-suite – CFO (DC). C-suite – Strategy (BM)
146 Advisory (SC)
147 Advisory (SC), C-suite – Legal (BT), C-suite – Strategy (BM), C-suite – Risk (CO), C-suite – CFO (DC), Service Provider (MoK), Service Provider (RB)

time.'[148] Such capacity can also be redeployed to 'hiring cleverer and more skilful people.'[149] Thus, whilst in many instances automation is used to eliminate roles – in other instances it is a strong tool for attracting, retaining and driving productivity from employees. That said, we ought to recognise that the axe does not fall equally and in such circumstances – certain individuals will be displaced whilst others will benefit from the resultant ways of working.

4.6.4 Organisational Resistance

Unsurprisingly leaders highlighted that the increasingly rapid adoption of automated decision making and decision support systems in organisations is leading to a range of resistance behaviours from the existing workforce. There are both macro and micro concerns in relation to the impact on human labour – driven against a backdrop of the likes of Susskind who is noted to be 'bullish on technology and bearish on human beings'[150] and one COO who commented that we are in danger of human agents becoming 'a bit irrelevant at some point.'[151]

Whilst people naturally 'don't like what they don't understand'[152] – the resistance here is borne largely out of observed impact. Efficiency results in a reduction of manual effort. From one advisory partner who highlighted a £100 million reduction in contact centre costs and an associated 21% reduction in head count[153] to a Service Provider who highlighted that an automated marketing solution had reduced 5,000 jobs[154] - the number of use cases resulting in material reduction is increasing at pace. At a micro-level, individuals are rightly concerned about the impact that such automation will have on their own livelihoods – and language used is highly emotive – with phrases such as 'unfair'[155], 'pride'[156], 'pain'[157] and 'uncomfortable'[158] used by leaders to describe reactions. One C-suite executive highlighted the tension as follows:

> "Change never comes willingly, right? You know, there's always resistance to change. People feel threatened that their jobs will not exist in the future. Yeah, there is resistance. What I always do tell them, some of my colleagues, fellow

[148] Service Provider (RB)
[149] C-suite – CFO (DC)
[150] C-suite – Legal (BT) NB: Personal associate with Richard Susskind
[151] C-suite – COO (DH)
[152] Advisory (TM)
[153] Advisory (SC)
[154] Service Provider (MoK)
[155] Advisory (SC)
[156] C-suite – Strategy (BM)
[157] C-suite – Strategy (BM)
[158] C-suite – Strategy (BM)

leaders, you know - this is the direction of travel for the industry. So, what you need to do is to try and retrain and retool to be relevant in the future. Being an obstacle right now might slow the process by a year or so, but you have a moving, huge ball coming down your way, you might as well get out of the way and find a way to have a different role that sort of contributes to this rolling ball. Or you are going to get squashed right?" C-suite – Risk (CO)

Such concerns will likely lead to resistance from impacted individuals with the potential to reduce the associated effectiveness of such programmes.

Whilst we may expect this reaction from the rank and file of an organisation. Resistance was also highlighted at more senior levels with automation impacting 'things like hierarchies of power.'[159] Advisory firms use spans and layers to assess organisational leaders influence and scope of accountability – directly correlating this to remuneration in many instances. The number of direct and indirect employees is something that certain organisational leaders value – driving 'perceptions of power and authority.'[160] Thus:

> "It's very unusual to find CFOs that want a lights out finance function. Because that means that CFO - we're not going to get there, right? But even if we get to a point where he's only got thirty percent of the people he had before. Suddenly you've gone from running a team of, I don't know whatever it is, eight or nine hundred people to a couple of hundred people. And you sit around the organizational table and you've got the smallest team. So, unless you're confident in your role and confident in how the organization affords you status, then it's going to be an issue." Advisory (SC)

The same was observed in media where centralisation and the associated automation was significantly reducing the authority of regional MDs resulting in 'their decision making going away and everything sort of shrinking from their perspective.'[161]

Thus, we can reasonably expect to see a range of resistance behaviours across organisations. Interestingly however, the nature of the automation introduced by an organisation materially impacts the nature of the resultant dialectic with employees and their ability to moderate outcomes. Where employees are simply displaced – resistance from those impacted is minimal

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[159] Advisory - SC
[160] Advisory - SC
[161] C-suite – CIO (SB)

– their roles are simply eliminated and there is little requirement for them to accommodate the offending technology. Augmentation is more nuanced. In such instances human agents are expected to work with technology to achieve outcomes – either by supporting processes or by utilising the decision support tools available. In such instances such agents have a far more significant impact on business outcomes achieved and must be carefully managed.

Whilst resistance is understandable – we have noted that the impact of automation does not fall uniformly across organisations. Despite fears, in certain instances, displaced capacity is not necessary eliminated. In various instances capacity is redeployed. So, despite the potential 21% reduction we described previously – 'the organisation hasn't taken anywhere near that 21% reduction. Because what it's done is it's allowed it to absorb new things at zero incremental new cost.'[162] As such although resistance occurs - there is a marked difference in reaction between 'those who are going to benefit from it'[163] – and those who, as one leader so eloquently narrated, get 'shafted by it.'[164]

4.6.5 External Accommodation and Resistance Gathering Pace

Leaders also highlighted that they felt there would be resistance from customers themselves – with dehumanized banking, medical practice, and expert advice[165] all highlighted as areas of potential resistance outside of organisational boundaries. As one leader posed 'will they at some point impose a limit by saying I don't want to do it. I don't want to completely to treated by a machine.'[166] There is a suggestion that this may be a generational issue and that those that have grown up valuing personal interaction may be more resistant than newer generations who perhaps value convenience over medium:

> "It would be a bold person who would dare bet against digitization hitting a limit any time soon and there being any limits to each new generation's acceptance of greater digitization and the services that they consume. And I, you know, my instinct says that there won't be any limits on it in terms of - if it works and there's value to it - they'll do it. It's the convenience factor, you know. It can be the case, that the perceived quality drops back a bit but the convenience factor trumps it all." C-suite – CIO (GC)

[162] Advisory (SC)
[163] C-suite – COO (DH)
[164] C-suite – COO (DH)
[165] C-suite – Partner (MH) & C-suite – Legal (BT)
[166] C-suite – CIO (GC)

The same leader went on to highlight the change in the music industry – with many now being prepared to sacrifice quality in exchange for value and convenience. Regardless of our sentiment, the customer angle is an interesting dynamic that must be considered in relation to external facing automation strategies and as a source of potential resistance.

The second macro theme highlighted was concern around the role of human beings generally going forward:

> "You perhaps start to move off into the philosophical debate about the longer-term. What's the role of people and where are the jobs for people and those sorts of things." Service Provider (RP)

One leader highlighted that they felt the impact could be so significant that new societal mechanisms may be required to 'give those displaced a means of support – where they get clothed and fed.'[167] In another instance the disruption of entire economies was considered via reference to low-cost processing locations such as India – where automation would disrupt the huge organisational infrastructure that has been established around low cost labour.[168] Again, we may reasonably expect that these macro concerns will have some impact on both employee resistance and public sentiment.

Thus, automation is heralded to materially disrupt organisations and society at large. Consequently, professional bodies, regulators and governments are taking an increasingly active role in the management of such impact. Our conversations highlighted that leaders are acutely aware of the impact of such intervention[169] – particularly those in regulated industries. Such interventions are expansive, covering a range of macro level ethical and almost existential questions and concerns. Whilst these questions have typically been the domain of philosophers and academics – the increasing encroachment of automation is forcing previously abstract debates to become far more practical. As we will discuss, the impact of such intervention is far from straightforward to assess.

Certain white-collar professions such as law, accountancy and medicine have historically been governed by professional bodies that set standards and oversee conduct. Historic practices and deliberate measures have in certain instances protected such professions from disruption – as highlighted through conversation with one General Counsel:

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[167] C-suite – COO (DH)
[168] C-suite – CFO (DC)
[169] C-suite – Risk (CO), C-suite – CIO (GC), C-suite – Legal (BT), Service Provider (KR)

"It's tricky because, in the US, the lawyers were very crafty back in the 1920s when these rules were put in place. The early 1900s, when you had sort of the expansion of large corporates that didn't want to pay these pesky lawyers, and they wanted to do it themselves. And lawyers realized they couldn't go to Congress and get a law passed because JP Morgan controlled Congress and Vanderbilt controlled Congress. So, what they did was they went to the courts, and they got the courts to enshrine these rules as part of the legal, ethical obligations that exist, and so they're, they're mandated by courts, which are unelected bodies, that the politicians can touch." C-suite – Legal (BT)

Such protections make it difficult for technology to disrupt traditional ways of working without the disrupting organisations 'running big risks'[170] as in the case of LegalZoom – an online provider of legal services – not necessarily dispensed by qualified lawyers. Given that the provision of legal advice by non-lawyers is technically illegal in the US the risks are obvious. This protection has resulted in professions being somewhat 'frozen in time.'[171] There are parallels in finance where one advisory partner highlighted that accounting standards have moved significantly in the last ten years – but to the point where they are 'not necessarily common sense anymore' and require 'significant judgement' to interpret.[172] Whether an unintended consequence or otherwise, such standards curtail more fully automated decision-making systems.

In turn, regulators are currently playing a 'very, very active role in the system and have the power to say you can or cannot do this.'[173] Such regulators are not necessarily blocking automated solutions per se, but strict review processes ensure complete transparency. The head of risk at an investment bank highlighted instances where machine learning had been deployed – but only post regulatory approval and subject to strict review on a frequent basis.[174]

"There are some pockets of machine learning where it optimizes itself, and that's on a trading desk, you know, so algorithms? You know, making trading decisions, trying to optimize P&L, that already exists, right? So, we have it in Exchange Traded Funds, we have it in the Algorithm Traded Funds. It runs itself, but even at that, the human, the expert needs to understand what it's

[170] C-suite – Legal – (BT)
[171] C-suite – Legal – (BT)
[172] Advisory (CV)
[173] C-suite – CIO (GC)
[174] C-suite – Risk (CO)

> doing. So, there is always a review process that happens at whatever cadence, you know, whether it's quarterly, or every 6 months, or every year. They need to go in and be comfortable that the decisions it took were the right ones. So, there has to be a peer review process.” C-suite – Risk (CO)

Thus, unfettered black-box processes will not be tolerated in regulated industries where any approved algorithm must be fully understood and operate in a consistent manner. The dialogue with regulators however was highlighted as a two-way learning process.[175]

Governments sit above all of this and are playing an increasingly active role in setting parameters impacting automation. Some of the decisions that are potentially being made or supported by machines have the ability to be ‘life-changing’[176] for individuals. At a high level, the impact of technology was likened to ‘capitalism versus socialism’ with technology on the far right hand side of the spectrum given its impartiality and ability to drive ‘disproportionate returns… to those that have not even ownership of the means of production, not even ownership of capital – but ownership of data.’[177] In other words, technology has the potential to drive an increasingly large gap between a small number of capital owners and the majority. Regulation and governments then will have a major role to play in ensuring that such societal impacts are managed in a considered fashion. In April 2021 the European Commission launched the European Union Regulatory Framework on Artificial Intelligence serving as a topical example of exactly the type of government intervention. The proposed legislation represents the first attempt to regulate artificial intelligence using a risk-based model and is expected to become more commonplace going forward.[178]

Interestingly however, whilst we may expect government and regulator intervention to be viewed negatively - it was highlighted as having beneficial impacts. Such intervention whilst curtailing and limiting certain activities also removes ‘ambiguity.’[179] In other words, regulations will clarify boundaries. The EU regulation for example sets out a risk-based framework:

[175] C-suite – Risk (CO)
[176] Advisory (TM)
[177] Advisory (TM)
[178] Service Provider (KR), Service Provider (RP)
[179] Service Provider (KR)

> "And essentially say there are certain things that are not particularly risky, and there are other things that are very high risk - so, high risk that we're actually going to ban them completely." Service Provider (RP)

In certain instances, legislation will help to legitimise activity and as such organisations may be more 'likely to push – because they know where the boundaries are.'[180] Thus we see a new dialectic of accommodation and resistance emerging that will both help set the boundaries – but equally provide assurance to adopting organisations.

4.6.6 Trust and Explainability are Key Issues in Driving Automation Adoption and Acceptance

A related theme that emerged strongly from discussion relates to the issue of trust and explainability in 'what is still quite embryonic technologies and capabilities.'[181] This is resulting in a 'whole industry springing up around auditing AI and automated things as a broader category.'[182] Whether that is trust in a machine delivering business outcomes or trust in safety critical environments – adoption looks set to be impacted by the ability to make models explainable and ensure reliable and consistent results.

We have observed previously the criticality of data in fuelling automation and this issue materially impacts the ability for machines to dispense advice in a way that is reliable and free from bias. As one advisory partner noted, the leading organisations invest significant effort in the analytical techniques that allow them to explain their models and pay 'almost as much attention to de-biasing inputs as they do to explaining outputs.'[183] They also invest significant effort liaising with both customer and internal teams to ensure that 'whoever is using the results of the machine, as it were, feels comfortable.'[184] Discussions highlighted running machines in parallel with human beings[185], building confidence over time[186] through demonstration of output or regularly auditing algorithms to ensure they are operating as intended.[187] What was clear from the leaders we spoke to was that no organisations were giving solutions free rein and adopting the more advanced forms of machine learning:

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[180] Service Provider (KR)
[181] Advisory (CV)
[182] Advisory (CV)
[183] Advisory (TM)
[184] Advisory (TM)
[185] Service Provider (RP)
[186] Service Provider (RB)
[187] C-suite – Risk (CO), C-suite – CIO (GC)

> “Even where we use automation - it has to replicate the activity of a human being and it is the human being who validates the automation algorithm and therefore that the results are correct. You know, it's still ultimately a human being. What the machine is not allowed to do is free run and self-learn.” C-suite – CIO (GC)

Thus, we saw a cautious approach being adopted – although we may reasonably expect this to accelerate and relax as we move forward.

Recent EU regulations place greatest emphasis on high-risk scenarios – particularly those that involve human safety. One Service Provider described work at Network Rail where machines advise on track maintenance. Such recommendations require engineers to attend high-risk situations based on machine output:

> “Network rail is not like the market research firm as soon as an engineer - it's called ‘boots on ballasts’ - as soon as an engineer steps onto the line, they're in danger. So as soon as AI tells them to step on the line, there's a certain amount of ethics around that. People have lost their lives. Two guys in Wales, unfortunately, died a couple of years ago because the data they had was incorrect, and they're on the wrong line, and there was a train coming the other way, and it killed them, unfortunately. You can see how it’s a massive enabler and will reduce risk, and that's why Network Rail are really happy because it will reduce risk and reduce cost. But they've got to trust an AI system now which is a big change for them really.”[188]

With high profile news coverage of automation failures – trust is likely be slowly built and hard earned. In certain instances, this is leading organisations to take a conservative approach and as one Service Provider noted ‘unless it’s a very black and white thing and you’re doing it within boundaries – always put a human being in the middle.’[189]

It is not just the adopting organisations that will need to learn to trust machines. Consumers may equally demand transparency – ‘making it clear to people where AI is being used, either entirely or partially in a decision-making process.’[190] Not only that but discussions suggested that such consumers have a right to understand how decisions have been made. In the case of

[188] Service Provider (MoK)
[189] Service Provider (KR)
[190] Service Provider (RP)

credit decisions for example – individuals have a right to understand why they have been rejected – regardless of the decision maker.[191] That said, as one CIO highlighted 'every generation is more tolerant of digital and have more trust in machines than the previous generation.'[192] The suggestion being that change will happen by degree – 'but it will happen.'[193] What appears to be happening at present is that trust is being carefully managed, explainability kept at the forefront of decisioning, and whilst that might limit the impact of automation and curb its immediate impact – it will lay the foundations for more rapid acceleration in due course.

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[191] C-suite – CIO (GC)
[192] C-suite – CIO (GC)
[193] C-suite – CIO (GC)

4.7 Summary of Results

We set out in Table 13 below, a summary of our findings, before going on to discuss the same in Chapter 5.

Aggregate Dimension	**Key Findings**
Data Fuels Automation of Decision Making	• Data is increasingly exponentially, driven by connected devices and increasingly digital operations. • Data becoming increasingly complex as a result of structured, unstructured and semi-structured data being generated and collected. • Organisations increasingly looking to monetise and exploit data – likened to the *new oil*. • Human agents struggle, unaided, to process and derive insights from data at high volumes. • Machines able to pioneer new insights from data. • Machines tireless and impartial – serve as coping mechanisms. • Reduced cost and accessibility of technology, coupled with increasingly aggressive new entrants, resulting in existential need to deploy technology effectively. • Increasingly data driven decision making focus from senior leadership and board. • Machines serve as coping mechanisms in the face of data volume and complexity. • Increasing the use of technology can promote data democratisation. • Recognition of a large number of decisions making domains where neither machines nor human agents are ideally suited in isolation – requires hybrid approach. • In absence of generic AI, narrow use cases can result in pilot proliferation and paralysis.

Aggregate Dimension	Key Findings
	• Recognition of the criticality of a robust data strategy.
Judgement and Experience Highly Prized in High-Stakes Decision Making	• Recognition that data alone is insufficient to inform certain organisational decisions. • Judgement and experience high-prized in relation to capital allocation decisions and other high-stakes organisational decisions. • Future is difficult to predict regardless of data quality and volume. • Human ability to creatively project the future can result in non-linear, exponential outcomes. • Human judgement can scale across contexts drawing upon analogous experiences. • Recognition that judgement is an intangible mix of skills and traits. • Express acknowledgement that human judgement can be prone to error and bias. • Human to human interaction critical in certain leadership situations and uniquely organic.
The Nature and Form of Accommodation	• Range of adoption drivers across industry and function resulting in increasing use of technology. • Industries and functions at differing levels of maturity - in part driven by competitive forces. • Automation increasingly displacing human agents – although human capacity may be redeployed rather than eliminated. • Increasingly closed loop systems in high maturity processes.

Aggregate Dimension	Key Findings
and Resistance to Automation is Evolving	• Broad recognition from leaders that technology deployment can have social and political consequences. • Deployment of technology in highly regulated industries seeing increasing focus from regulators regarding black-box techniques and machine learning. • Professional bodies in certain professions impacting deployment of technology. • Customer preference and habits impacting organisational decisions regarding technology deployment – but recognition that generational attitudes differ significantly. • Legislation increasingly impacting organisational decisions about technology deployment – offering both accommodation and resistance. • Trust and explainability likely to have significant impact on future deployment and use of technology.

Table 13: Summary of Results

Chapter 5: Discussion

5.1 Introduction

We began this journey motivated by an observation that organisational decision-making stood to be heavily disrupted by rapid advances in automation – and that the impact of such disruption is underserved in the existing literature. It is barely possible to go a day without reading about the transformative and disruptive influence of technology. We are told that self-driving cars will be roaming our streets as part of a $7 trillion market by 2050 (Gill, 2020) – complete with advanced decisioning systems that will need to navigate ethical, moral and practical decisions in collision scenarios (Awad *et al.*, 2018). Highly topical at the moment, we read about increasingly autonomous weapons of mass destruction that enable operators to remotely target areas using advanced technology (Horowitz, 2016) - with such abstraction raising serious questions about the impact of technology on moral agency (Bigman et al., 2019). Finally, within medicine we read about technology 'that can perform the more complex tasks of pathologists and, in some instances, with superior accuracy' (Jha & Topol, 2016, P.2354). In all three fields decision making has been fundamentally disrupted by technology – reframing the way in which we think about the boundaries between human and machine intelligence. This trend is only set to accelerate, as acknowledged by Berente et al:

> "How to go about making decisions with computing has been a central, and at times controversial, idea throughout the history of computing. However controversial, AI is fundamentally about making decisions autonomously" (Berente *et al.*, 2021, P.1435).

Yet organisational decisioning making, arenas within which human judgment has long been prized and served as a key differentiator, are wholly underserved. Notwithstanding that fact it is increasingly clear that 'expectations and uncertainty about how artificial intelligence (AI) will change the workplace appear boundless' (Fügener *et al.*, 2021, P.1527). This is perhaps even more surprising when we consider the fact that organisations spend billions of dollars every year on automation, and industry is increasingly disrupted by digital native organisations that reimagine business outcomes. As such we believe the as yet unanswered question is simply: given recent advances in automation where and to what extent should leaders consider deploying machines to support decision making in large organisations?

We began by exploring the extant literature, before engaging in qualitative research with leaders to redress the perceived omission, as advocated by Bailey & Barley (2020) and Berente et al (2021). In this section we briefly recount the existing literature – before discussing the results of our interviews against such backdrop.

5.2 A Recap of the Existing Literature

Unaided human decision making is a fundamental and recurrent human activity (Hogarth, 1989). Utility theory suggests that rational decisioning making entails the assessment of all possible outcomes before selecting the choice that results in the greatest utility. Yet, in reality, the unaided human decision maker has neither the luxury of unlimited time nor unlimited processing power – essential components if one is to make an economically rational decision (Todd & Gigerenzer, 2001). As such, bounded human agents satisfice in response to real world complexity (Simon, 1945) – using heuristics short cuts (Gigerenzer & Gaissmaier, 2011; Gigerenzer & Goldstein, 1996; Gigerenzer & Goldstein, 2011) and intuition (Evans, 2010). Whilst these techniques allow unaided agents to navigate real world scenarios – cognitive limitations, inability to adequately discern between type 1 and type 2 processes (Evans, 2010) and the impact of emotions such as regret can lead to 'severe and systematic errors' (Kahneman, 2003 P. 1452). In the absence of viable alternatives, we may have historically celebrated the perception that rational decision making is a 'unique achievement of our species' (Evans, 2010 P. 323) – but in actual fact one might argue that human unaided decision making is rarely as rational as many of us might like to think (Agrawal *et al.*, 2019; Kahneman, 2003; Kahneman & Tversky, 1984; Kleinmuntz, 1990). As such, we are left dissatisfied with the direction provided by the literature regarding where and why unaided human decision making should be deployed if alternatives were to become available.

The parallels between individual and organisational decision making are somewhat striking. Organisations are legal fictions (Jensen & Meckling, 1976), a nexus of contracts (Fama & Jensen, 1983) that exist to maximise utility for their owners. As such decision making recurs throughout organisations which can themselves be considered as 'information processing and decision rendering systems' (Cyert, 1963 P.19). As organisations grow in size and complexity this decision making becomes challenging given the potential for misalignment between equity owners and the managers appointed to operate the firm on their behalf. Agency conflict occurs given the potential for managers to make decisions which maximise their own, rather than the owner's utility (Cyert *et al.*, 1956; Cyert, 1963; Eisenhardt, 1989; Hendry, 2005; Jensen & Meckling, 1976), an eventuality that economic rationality all but assures. Organisational decisions are made in the absence of perfect information, and we find that organisations are bounded in equivalent ways to individual decision makers, resulting in bias (Foss, 2003). Much has been written about how such balance may be redressed through inter alia operating procedures (Cyert, 1963; Feldman & Pentland, 2003; Van Ees *et al.*, 2009) and board stewardship (Fama, 1980; Fama & Jensen, 1983). However, technology all else being equal looks set to disrupt and transform the way that organisations think about data transparency and organisational decision making. Despite that we find that the topic is underserved in the literature. We consider there to be an open question concerning the extent to which organisations should accept satisfactory outcomes if more economically rational outcomes could be achieved by alternative means.

Historically, the foregoing observations were interesting but somewhat abstract given the absence of alternatives to human decision making. We observed that automation has experienced winters and springs (Duan *et al.*, 2019) – with the expert systems of the 80s falling foul to a range of epistemological limitations which saw them fail to fulfil their potential in all but the most repetitive scenarios. Expert knowledge until recently has been protected Polanyi's paradox, epistemological challenges (Dreyfus, 1972) and the frame problem (McCarthy & Hayes, 1969). In recent years however, advances in automation have seen machines encroach into traditional human domains. Machines, powered by almost unlimited computing power, advanced machine learning algorithms (Jarrahi, 2018) and an array of sensors are increasingly well adapted to the data rich environment that now characterise modern organisations. Machines are moving from digital realms to increasingly exerting physical materiality (Berente *et al.*, 2021). However, black-box technologies have given rise to issues of trust and transparency which threaten to curb progress (Berente *et al.*, 2021; Bowonder & Miyake, 1992; Rudin, 2018). We find that the extant literature fails to adequately assess the likely impact of such automation in large organisations and is almost entirely devoid of materials covering the perspective of the associated organisational leaders whose power and influence will likely drive scale and breadth of adoption (Bailey & Barley, 2020). We find limited practical or theoretical guidance regarding where such automation should be deployed and why – despite recent calls.

Edwards et al (2000) suggests that we consider organisational decision making through three lenses – operational, tactical, and strategic. This was reinforced by Cyert et al (1956) who proffer that repetitive, well-defined problems lend themselves to rational decision making and thus automation. Organisational decisions are characterised by complexity, uncertainty and equivocality (Jarrahi, 2018). As such, organisations have invested in decision support tools for decades in an attempt to drive better business outcomes. Data is increasing exponentially, and black-box technology is enabling machines to increasingly augment or displace human agents.

Pickering's (1993) mangle of practice helps to bring together the various streams of our narrative review by highlighting the dialectic between material and human agency that takes place within organisations. Automation is both accommodated and resisted, resulting in emergent business outcomes that can be difficult to predict in advance. We question whether the dialectic has been impacted by recent changes in regulation and whether the nature of material agency had been impacted by black-box technology.

5.3 Open Questions, Anomalies and Our Approach

Our scoping literature review identified a number of open questions, whilst disciplined imagination (Saetre & Van de Ven, 2021) lead to the identification of a number of perceived anomalies. Fundamentally we sought to understand, where and to what extent leaders should consider deploying machines to support decision making in large organisations in light of recent advances in technology.

Using abductive inference, we conducted a purposeful sample of organisational leaders to gain a greater understanding of their knowledge, attitudes, and practices in relation to the automation of decision making. This approach addresses Bailey & Barley (2020) entreaty that we seek to understand the perspectives of those with the power to shape and drive adoption of intelligent technology. Rubin and Rubin (2012) responsive interviewing technique served as the method to interview 25 organisational leaders across a range of industries. Our intention was to extract depth through discussion. The resultant 170,000 words of transcript that resulted from such discussions suggests that we were successful in our endeavour. Our results provide unique insight. We go on now to discuss these insights in light of the extant literature.

5.4 Discussion of Findings

In support of Jordan & Mitchell (2015) we find that organisations are seeing an exponential increase in data – which was likened by one leader to the 'new oil.'[194] We consider this a very apt analogy[195] and concur with the view that in its raw form data creates no value or insight –

[194] C-suite – CEO (RH)
[195] We note comment from our feedback workshop which highlighted challenges with this analogy – particularly given the socio-political issues associated with oil. Whilst electricity was proffered as an alternative analogy – we consider the two analogies to be subtly different and believe each has an explanatory role to play.

but once processed it can be incredibly valuable. The sheer volume of sensors and collection points has increased materially in recent years. We heard how Thames Water have deployed an array of sensors in response to increasingly large regulatory fines, whilst National Rail have deployed sensors to assess the health of its tracks. In keeping with Al-Fuqaha et al's (2015) observations, these devices are resulting in organisations creating more information than ever through their increasingly connected digital operations. Our discussions with leaders suggest that data awareness is at an all-time high and there is an increased focused on exploiting the same. This extends throughout the organisational hierarchy with the board members we spoke to heavily focused on data driven decision making. This is in keeping with the findings of Jingyu et al who note that 'although prior IS research has shown that boards do not pay attention to IT, we argue that the opposite is true in the context of AI orientation' (Jingyu *et al.*, 2021, P.1604). We note however significant differences in organisational competence in relation to data strategy. Unsurprisingly traditional organisations in many instances struggle with legacy technology debt. Organisations such as Amazon Go have the luxury of reimagining the entire end to end process of high street shopping unencumbered by existing infrastructure and investments.[196]

However as the volume of data has increased it has gradually reached the point where unaided bounded rational (Simon, 1945) human agents struggle to process and extract meaning from the resultant data sets. In the example of Thames Water – the data itself proved insufficient to drive business outcomes. Human engineers struggled to process data sufficiently calling for an automated decision support layer:

> "So again, the solution was automated – typically how they were doing it was you had all these engineers who would get information from all these water pipes with pressure sensors and things like that on them. But all that data would come into an excel and the engineers would start to look at it. 'We think there might be a problem here' and then they'd go and dig up the ground. Then they'd say 'No, its not there. I think its somewhere else.' We put an AI layer on top of that to analyse the data and again just pinpoint, based on probability, where we think the leak is coming from – with a geospatial kind of database on top of it. That saved a huge amount of money in leaks." Service Provider (KR)

[196] Advisory (CV)

Although heuristic principles may be deployed to help such agents to make decisions[197] – the reality is that for the majority of human agents the ability to process such vast amounts of data is beyond their cognitive ability. Heuristics simply cannot help agents to assess such vast amounts of data without material compromises being made. In the face of paralysing amounts of data – unaided decision makers would likely rely on less rational, intuitive short cuts. Leaders highlighted equivalent challenges in relation to the Serious Fraud Office[198], medical diagnosis[199] and legal discovery.[200] Can organisations afford to 'satisfice' (Simon, 1945) and make decisions that are 'good enough' (Van Ees *et al.*, 2009, P.312) driving 'satisfactory profits' (Cyert, 1963, P.9) if the competition are looking at ways to maximise?

This issue is compounded for organisations when we consider that data presents a multi-faceted challenge. Not only is the volume of data increasing exponentially – but organisations are increasingly collecting structured, semi-structured and unstructured data. Several leaders observed that human agents have historically been accustomed to working with structured data[201] that can be readily tabulated and analysed. However, in recent years organisations have seen an exponential increase in both semi-structured and unstructured data – with organisations hedging their bets and collecting as much data as possible in the hope that they can eventually extract value – even if the value is not immediately apparent.[202] Such data is increasingly collected as an ancillary to an organisation's operations – in part as a result of digital ways of working that enable more information to be captured by a variety of means. We found that the ability to process semi-structured and unstructured data can be a source of significant competitive advantage and lead to pioneering new applications and ways of working. One leader cited the example of Google's work with Moorfield hospital where they inadvertently identified that AI could predict the age and sex of a person from a retina scan with 96% accuracy versus human clinicians somewhat paltry 30%.[203] We also saw how media companies are using machines to identify trends from social media and other digital sources that provide insight that would be impracticable to collect via organic means.[204] Unaided, opportunities to capitalise would go undiscovered and the potential of data would go unfulfilled. This is

[197] We note unsurprisingly that heuristics were not raised in discussion with leaders – although multiple references were made to intuition and bias.
[198] Service Provider (FL)
[199] C-suite – CEO (RH), C-suite – CIO (GC)
[200] C-suite – Legal (BT), C-suite – CFO (AS)
[201] C-suite -CEO (RH). C-suite – CIO (GC)
[202] Service Provider (KR)
[203] C-suite – CEO (RH)
[204] C-suite – CIO (SB)

consistent with the recent work of Jingyu et al (2021), Sturm et al (2021) and van den Broek et al who found that 'by computationally detecting patterns in large datasets, algorithms can uncover hidden relationships that are far too large and complex for humans to decipher' (van den Broek *et al.*, 2021, P.1559).

In contrast to organic agents, machines are perfectly adapted to process vast amounts of data. As we have commented they do not tire.[205] Such machines process data with perfect impartiality (Anderson & Anderson, 2007). Machines are well suited to identifying patterns across both immense volumes of data and across the full spectrum of unstructured through to structured formats. Unlike human agents who satisfice in response to complexity – machines will continue to run processes (including heuristic processes) tirelessly – identifying patterns that are indiscernible to human agents. Furthermore, we found such methods have the potential to increase data transparency and support data democratisation. The challenge then, as neatly articulated by one service provider, is that organisations increasingly want:

> "Chief data officers who can either give them data as a service or data as a product that enables them to make better decisions. They want to build a process around those that reduces human bias and cognitive individual biases – to take the decision away from one person and put it in the hands of a system, ultimately driving better outcomes." Service Provider (RB)

The explosion of cloud technology and continued impact of Moore's Law has seen technology become increasingly accessible. Every leader we spoke to was considering both data and how to exploit technology to their advantage. As observed by Berente et al (2021) 'one could argue that managers delegate an ever-increasing set of decisions and related tasks to IT' (Berente *et al.*, 2021, P.1439). The question then remains where and how extensively to deploy such machines (Newell & Shanks, 2014) and what, if any, 'engineering bottlenecks' (Frey & Osborne, 2017, P.24) or 'unique human knowledge' (Fügener *et al.*, 2021, P.1528) may impede progress.

In response to that question, we may consider Dreyfus's assertion that human agents are perfectly adapted to large world complexity given physical proximity to it (Dreyfus, 1972). Dreyfus's epistemological defence foresaw technical limitations given the ethereal and disembodied nature of machines – which were entirely dependent on human operators for data

[205] C-suite – CEO (RH)

and context. However, the burgeoning of data referred to above has resulted in the creation of what we might start to consider - digital worlds. Worlds composed predominantly of bits and bytes. Worlds that have dizzying amounts of data points in a raft of different forms. In such a world we may flip Dreyfus's defence on its head. In such environments human cognitive, temporal limitations and propensity to use intuitive shortcuts become an inhibitor - whilst machines, by contrast, are perfectly adapted to such environments. In such a world there is limited room for intuition, to satisfice, to limit learning through frailties such as regret. Such a world calls for cold, tireless intellect that can process vast volumes of data with perfect impartiality. Such worlds are entirely ethereal and well served by software that can match such state. In such worlds data is king. In such digital environments we might argue that machines are *in-the-world* in a way that organic human agents cannot match. In such worlds machines may well serve as Newman et al's 'perfect agent' (Newman *et al.*, 2019, P.20).

Not only do we find that new digital worlds are being created and expanding rapidly – where data and perfectly adapted machines dominate – but equally that Dreyfus' original defence against machines in the organic world is also starting to weaken. In the 1980s machines were very much abstracted from the world that they sought to model and analyse – computers sat in server rooms entirely reliant on human agents to feed them data. In the last 40 years the world has moved on at pace. As noted by Brynjolfsson et al:

> "DNN Software can be extended to new domains formerly closed to digitization by the high cost or impossibility of writing explicit maps of inputs to outputs and policies" (Brynjolfsson *et al.*, 2018, P.44).

As we have noted, sensors are becoming increasingly ubiquitous, and the internet of things is connecting devices in ever more complex ways to drive data insight:

> "The advance of the internet and communication technologies significantly scale up AIs self-learning ability to the entire network rather than individual machines" (Huang & Rust, 2018a, P.161).

Consequently, we can argue that machines are now *in-the-world* and have physical form. By world in this context, we mean the physical world – the organic world of matter. Not only are such machines able to extract and make sense of information about this world – but they are able to draw insight that again, would likely be beyond most humans. Smart watches for example monitor blood pressure, sleep patterns and a myriad of other data points to help inform their user about their health.[206] As observed by one leader, we are surely rapidly approaching a point where doctors no longer need to ask their patient about their eating and drinking habits – a closed loop system, fuelled by connected devices, will provide factual accounts fed by sensors.[207] Machines in this sense have the ability to exist in both the physical and the digital world – and we should note that 'an entity's agency in each of these worlds is determined by how much causal influence it can exert in each one' (Newman *et al.*, 2019, P.5).

However, being *in-the-world* is not sufficient to overcome the totality of Dreyfus epistemological defence. Part of human adaptability relates to so called 'conceptual revolutions' (Dreyfus, 1972, P.290). We might think of this as continual learning and adaption based on context – reflecting the view that there are no fixed responses. Machine interaction with the organic world and increasingly being situated in context – potentially overcomes the ability to manage fluents. However, if human agents are required to code every potential response, then such machines would continue to be inhibited by the potentially unlimited number of real-world contexts against which responses would need to be established. Thus, we would likely encounter much the same challenge as expert systems of old – the original frontiers of which were 'determined through deterministic, explicit logic coded into technology' (Berente *et al.*, 2021, P.1441).

Against this backdrop, machine learning is critical if machines are to overcome the historical challenges faced by traditional rules based expert systems which are reliant on human knowledge engineers (Duan *et al.*, 2019). Although well suited to closed worlds (Lee & Moray, 1992) rule based systems make it inefficient and in some instances impracticable to refine machines at pace when working across vast data sets. The advance of machine learning enables machines to impartially learn through feedback loops to improve accuracy, process, and drive outcomes. As one service provider commented 'machine learning is really powerful because it's all about the power of repetition across more and more data.'[208] This capability is critical if machines are going to reach their full potential. The challenge however, is that this can result in black-box processes which reduce transparency and can inhibit trust (Rudin, 2018). Whilst we have noted that younger generations appear to be more tolerant of such techniques[209] – we must acknowledge that at present resistance to such methods is likely to inhibit progress. If we

[206] C-suite – CIO (GC)
[207] C-suite – CIO (GC)

[208] Service Provider (FL)
[209] C-suite – CIO (GC), C-suite – Partner (MH), C-suite – CEO (RH), C-suite - CFO (AS)

insist on machines being trained and tweaked by human agents – we are unlikely to see the pioneering benefits that could otherwise result. We will return to this point subsequently.

Berente et al argue that automation fuelled by AI differs from previous generations of technology by way of their 'autonomy, learning and inscrutability' (Berente *et al.*, 2021, P.1437). The authors complement our findings suggesting that machines increasingly 'act in the world in a way that has material outcomes' (Berente *et al.*, 2021, P.1437). This autonomy is supported by learning capability that enable the same to encroach into ever more complex decision-making settings. However, these two inter-related facets result in inscrutable processes which give rise to concern over black-box techniques. The result of the foregoing is that managers will increasingly need to make difficult 'decisions with the technology and about the technology' (Berente *et al.*, 2021, P.1439).

In the absence of guidance as to how such decisions should be made, we found strong evidence from leaders that automated use cases run the risk of proliferating. Leaders suggested that we are a long way from general artificial intelligence. This is in keeping with Brynjolfsson et al who state that "we are far from artificial general intelligence (AGI) which would match humans in all cognitive areas" (Brynjolfsson *et al.*, 2018, P.43). As Newman et al note:

> "When an agent's initial attempts to pursue some goal are thwarted, that agent will spontaneously and flexibly configure its behavior so as to continue to pursue its goal. A human need not stop at the ground – they can retrieve a shovel, and perhaps a jackhammer or a drill if called for (if they really want to!). This is to say, when an agent is engaging in goal-directed activity, its behavior is robust against perturbations and obstacles in a way characteristically not present in animate objects" (Newman *et al.*, 2019, P.3).

Consistent with Berente et al who highlight that 'any particular AI model may focus on relatively minor prediction decisions' (Berente *et al.*, 2021, P.1435) we found that the inability for technology to transcend use cases can result in a 'proliferation of pilots.'[210] Whilst this in and of itself is not necessarily an inhibitor to adoption it does mean that organisations need to carefully consider their investments.

Further, our discussions highlighted a number of 'engineering bottlenecks' (Frey & Osborne, 2017, P.24). We found that the most significant decisions made by organisations relate to

[210] Partner (TM)

capital allocation.[211] In other words, decisions concerning how and where organisations should deploy their assets. Decisions regarding acquisitions and divestments exemplify this decisioning space. We found that such decisions call for organisations to anticipate and predict the future. This requires a creative process of abstraction beyond hard data. Jingyu et al highlight that automation is not well suited to 'creating innovation across the entire spectrum of novelty' (Jingyu *et al.*, 2021, P.1467) – suggesting that it is incapable of generating new ideas where 'little or no data are available' (Jingyu *et al.*, 2021, P.1467). Whilst data tells us about what has occurred in the past and may assist in linear forecasting – in many instances it is deemed insufficient by leaders to adequately make high-stakes future facing decisions.[212] Interestingly, despite the fact that such investments are the highest stakes decisions made by organisations they were highlighted as examples where significant judgement was required and where success was far from guaranteed.[213] (Davenport & Ronanki, 2017)

The acquisition of Pixar by the Walt Disney Company in 2006 serves as a good example of this phenomenon. CEO Bob Iger recounted his decision making process in The Ride of a Lifetime (Iger, 2019). Having first visited Pixar in 2006, Iger, and was immediately taken the subjective value of the organisation:

> "I felt breathless as I described to Tom the level of talent and creative ambition, the commitment to quality, the storytelling ingenuity, the technology, the leadership structure, and the air of enthusiastic collaboration – even the building, the architecture itself" (Iger, 2019, P.140).

Disney had access to the most sophisticated decision support aids and advisors – experts in company valuation. These experts seemingly advised against the acquisition – including Iger's own team, Disney's corporate bankers and the board. By his own admission, 'on paper the deal didn't make obvious sense' (Iger, 2019, P.140). Yet Iger saw something in the culture and team at Pixar that he believed transcended the numbers and rational analysis:

> "As with everything, the key is awareness, taking it all in and weighing every factor – your own motivations, what the people you trust are saying, what careful study and analysis tell you, and then what analysis can't tell you. You

211 C-suite – CFO (AS), C-suite – CFO (BF), C-suite – COO (DH), Board Member (AH), Board Member (HB)
212 Board Member (AH), Board Member (RF), C-suite – CFO (AS), C-suite – CFO (BF), C-suite – COO (DH), Advisory (MH)
213 Board Member (AH), Board Member (RF), C-suite – CFO (AS)

> carefully consider all of these factors, understanding that no two circumstances are alike, and then, if you're in charge, it still ultimately comes down to instinct" (Iger, 2019, P.141).

Despite the hard data Iger was able to convince the board to support the acquisition. History suggests that the Pixar acquisition was an overwhelming success and a game changing decision for Disney. Strikingly however, purely rational analysis of the numbers would not have supported the decision. Disney's success in this instance was down to the instinctive decision making and judgement of one leader.

The foregoing narrative resonates powerfully given the insight we gained from leaders. One board member stated, 'if you just look at the numbers alone – you wouldn't do anything quite frankly.'[214] This recurred throughout discussions – highlighting a sense that there were certain decisions that cannot be made on a purely analytical basis. In fact, even where decisions were made in such a manner you would likely be 'precisely wrong because there's always some element that you miss.'[215] Thus, human judgement and experience continue to be prized in such high-stakes decisioning. Not only that, but there was a suggestion that in a future state where automation has broadly levelled the playing field, where data and technology are ubiquitous and democratised, that such judgement could become a key differentiator.[216] Exponential outcomes are rarely achieved by following a linear path. Clayton (1997) highlights this point in the Innovators Dilemma, highlighting that organisations following a linear curve will eventually be overtaken by disruptive competition that reimagine the future.

Yet judgement remains somewhat resistant to definition with phrases such as intuition, gut, EQ, common sense, wisdom, and creativity recurring throughout our discussions. It is paradoxical that despite widespread recognition from the leaders that we engaged, that such soft decisioning skills can lead to bias, self-interest, and systematic error – that they are so prevalent in the highest-stakes decisions that organisations make. Despite decision support tools and sophisticated advisory – ultimately the most significant decisions made by organisations seemingly come down to instinct, intuition, and judgement. We might also add that whilst there are examples of great decisions being made on such a basis – there are equally a litany of abject failures. As observed by one board member 'everybody knows that acquisition is a high risk. The rule of thumb is that a 3rd will fail, a 3rd will be successful, and a 3rd will

[214] Board Member (AH)
[215] C-suite - CFO (AS)
[216] Partner (SC)

be kind of average.'[217] The fact that a third of all high-stakes acquisition will fail is a significant omission given that organisations are largely considered to exist to maximise utility for their shareholders.

The second significant engineering bottleneck that we identified related to human-to-human interactions. As one board member observed 'all judgements around people, which are absolutely critical, are soft.'[218] Even within the heavily automated financial services sector there is still a place for relationships 'that it has cultivated over years and years and years.'[219] These relationships fall into the low volume, high impact category. In a similar manner we observed that whilst a lot of legal work is capable of being automated, the residual elements are all about people 'if you think about what the law really is, it's humans organizing things for humans.'[220] Thus, unlike machines 'we are embodied beings that inherently exist in a web of relations within political, historical, cultural and social norms' (Newman *et al.*, 2019, P.7).

We have commented previously that machines are well suited to analysing rafts of different types of data and finding patterns in unstructured sources. Yet, humans are particularly well adapted to reacting to and reading others human beings. As one leader commented:

> "There is something about that sort of gut instinct of whether someone's telling the truth, whether you feel like this person is reliable - whether it's body language, whether it's small facial variations. You know, heartbeat - there's studies showing that one of the reasons it's so hard to interface on zoom is that when you're actually in person your brain can actually read in some bizarre way - heartbeat, blood pressure, all kinds of nonverbal clues coming from across the table - that you're not picking up on a screen right, and certainly an AI would have trouble deciphering." C-suite – Legal (BT)

In a similar manner, another leader described how doctors treat patients – making a myriad of assessments on the patient's health and mental state before beginning any form of structured examination.[221] This is consistent with Autor et al who stated:

> "For example, research in cognitive science suggests that a trained physician holds in mind models of the body's functional systems and allow her to make

[217] Board Member (RF)
[218] Board Member (RF)
[219] C-suite – Risk (CO)
[220] C-suite – Legal (BT)
[221] C-suite – CIO (GC)

> educated guesses about the sources of maladies based upon discrepancies between the model and the observed behavior of the patient" (Autor *et al.*, 2003a, P.7).

Although machines may continue to encroach into this space over the coming years, with sensors enabling them to read human reactions with greater accuracy – it would seem likely to be some time into the future (Youyou *et al.*, 2015).

Our findings are consistent with a paper by Sampson looking at the impact of automation on professional services who noted 'two professional job requirements that are assumed to also be barriers to automation: creativity and interpersonal skills' (Sampson, 2020, P.128). In the professional task-automation framework proposed in response Sampson proposes that *interpersonal expert work* and *interpersonal work* may effectively be augmented by technology but not replaced. Our findings are broadly consistent with this work – although our research is specific to one particular task – decision making – whereas Sampson makes broader claims for high order skills in a general capacity. We are equally consistent in our conclusions that 'wise professionals will proactively assess the skill requirements of the various tasks within their jobs, make adjustments and task reassignments as necessary, and thus be more prepared for the upcoming onslaught of AI and other automation technologies' (Sampson, 2020, P.136). Our proposed diagnostic tool supports organisational leaders with such assessment.

Consistent with the foregoing, Huang & Rust (2018) suggest four different intelligences in relation to service-based tasks, namely, mechanical, analytical, intuitive, and empathetic. The authors offer a table in their paper setting out decision making behaviours within each of their identified intelligences. The paper proposes that rational decisioning making be applied to analytical intelligence, bounded rational decision-making to intuitive intelligence and that emotions are incorporated within empathetic intelligence. The latter requiring 'soft empathetic professionals that require social, communications, and relationship building skills' (Huang & Rust, 2018a, P.157). Disappointingly for our purposes the authors make no attempt to expand upon these bulleted points and to account for the basis of their position. In particular we question whether bounded rational decision making applies to intuitive intelligence and exactly what should be inferred from this statement. We have argued intuitive decision making belongs to system 1 whilst rational decision making belongs to system 2. This leads the authors to a potentially erroneous conclusion that 'in training students, such programs should emphasise creative thinking and intuition in interpreting data or making decisions rather than training students to be data and analysis machines that can lose their importance sooner' (Huang & Rust, 2018a, P.168). Whilst we agree with the sentiment that soft skills have greater significance in an automated future – we question the extent to which intuition can be taught and would in any event guard against the negative consequences of encouraging the use of intuition across broad contexts. They have a place – but that place ought to be carefully assessed and consciously determined.

In any likely future, machines are unlikely to have it all their own way and will likely face resistance. Pickering's (1993) mangle of practice suggests that technology is subject to a dialectic of accommodation and resistance. Traditionally such resistance has predominantly come from the impacted individuals – primarily those being displaced. Increasingly however, where automation displaces – it displaces absolutely – requiring no real support or input from the vast majority, if any, of the displaced teams. A myriad of examples of displacement were highlighted through our discussions. Whilst organisations in various instances repurpose capacity or point staff to higher value-added activity – there can be no question that in many instances employees are simply severed. The business drivers associated with automation are such that organisations will increasingly have limited choice but to adopt technology if they are to remain competitive. Thus, the dialectic is pushed further up the organisation hierarchy than we may have been accustomed to in the past.

Where machines provide decisions upon which human agents are obliged to act, we witness a subtly different form of resistance. In the example of National Rail – engineers entering safety critical environments were sceptical about machine inference. In keeping with Lee & Moray (1992) and Rempel et al (1985) we find that trust plays a critical role in such contexts and is easily eroded through negative events – despite the fact that human agents themselves are rarely perfect. Thus, human agents hold machines to higher standards and are more likely to question and resist instructions originating from a machine – particularly in relation to safety critical environments. A form of algorithm aversion (Gill, 2020).[222]

At more strategic levels of an organisation machines provide decision support – typically information and data to help inform high-stakes decisions. We have noted however that such decisions ultimately rest in the hands of the most senior executives in the company and highlighted that in such instances data is often considered to be insufficient to fully inform decisions. As such we saw limited resistance from such leaders, who welcomed the additional

[222] Note that this theme came out strongly in our feedback workshop.

input – but who seem unlikely in the near future to rely exclusively on the same. Automation is yet to seriously encroach into this space. Given the existential impact of automation at tactical and operational levels, and the absence of any immediate threat to their own authority - we can reasonably expect senior leaders to promote automated decision making – particularly when facing competition from digital natives or when dealing with high volumes of complex data.

That said, automation looks set to materially disrupt at a macro level. Consequently, we see evidence that resistance will increasingly come from sources external to the organisation itself. We found strong support that resistance increasingly originates from customers, professional bodies, regulators, and governments. Disruptive digital first organisations have pushed the boundaries in recent years – forcing more traditional companies to respond in order to remain competitive. Within financial services we see regulators playing an active part in defining the parameters within which machines can operate – limiting black-box processes and ensuring continued transparency through human replication of processes in many instances.[223] As Charlwood & Guenole note, 'model explainability is an active and fast-developing field of research in artificial intelligence' (Charlwood & Guenole, 2022, P.11). Whilst we found instances where machine learning was permitted by regulators the associated checks and balances result in relatively modest application. Furthermore, recent draft regulation from the EU has for the first time enshrined in law the guard rails that will govern use of automated solutions. This is a point highlighted by Charlwood & Guenole in relation to HR:

> "In Europe, the European Commission is looking to build on the protections for workers provided by the General Data Protection Regulation (GDPR) through new regulation on AI, a draft of which was published in April 2021. The regulation posits that the use of AI for hiring, promotions, and pay decision making and for management and control of workers is 'high risk' requiring significant safeguards to be put in place if AI is to be used for these purposes" (Charlwood & Guenole, 2022, P.9).

In a similar manner professional bodies are likely to impact automation. Through discussion, leaders recounted how the legal professional has traditionally created defences against disruption – through regulating those able to dispense legal advice in the US for example.[224] Similarly, financial accounting standards call for significant judgements to be made – beyond

[223] C-suite – CIO (GC), C-suite- Risk (CO)
[224] C-suite – Legal (BT)

the capability of laypersons and promoting financial expertise.[225] Such judgments mean that formulaic approaches are challenging and leave room for expert opinion. Although both professions are facing increasing disruption from automated solutions and digital start-ups – we are likely to see continued accommodation and resistance from such sources. This is a point highlighted by Sampson who noted that laws may require licensed professionals to do certain tasks even though technology would allow semi-professionals or customers to effectively perform those tasks' (Sampson, 2020, P.136).

We also noted acknowledgement from leaders that customers themselves may inhibit the advance of automation with concerns regarding the dehumanisation of various consumer experiences from banking through to expert advice. Although Sampson highlights that 'if a law firm invests in technology to allow paralegals to perform professional-quality patent searches, should the client care?' (Sampson, 2020, P.135) – ultimately the consumer, when faced with choice, will determine their own comfort level. Focus on value and convenience over experience may help to overcome resistance – as seen in the music industry where consumers have been prepared to trade the quality of audio – for the convenience of carrying thousands of songs on a single device.[226] Regardless, customers and consumers will likely both accommodate and resist automation as we move forward – it being noted by leaders that there will likely be a generational difference in tolerance for change.

Thus, we observe a new form of mangle. In addition to technology being mangled through localised internal dialectics – we see accommodation and resistance shift outside of individual organisational contexts and into larger domains. That said, whilst we note that legislation and guidance from professional bodies undoubtedly curtails certain activity – for others it legitimises practice by helping organisations determine 'where the boundaries are.'[227] In other words, organisations are likely to pursue automation within set parameters – de-risking and legitimising such practices. Thus, on the one hand legislation will prevent more extreme applications but potentially accelerate roadmaps for those that have historically had more modest ambitions.

Finally, we could not pass up the opportunity to discuss the potential post-humanist impact of recent advances in technology on the nature of material agency. We have noted that data is growing exponentially creating digital environments where perfectly adapted machines will

[225] C-suite – Partner (MH)
[226] C-suite – CTO (GC)
[227] Service Provider (KR)

dominate. We have also noted that connected devices are increasingly reducing the organic world to bits and bytes. With the advent of machine learning and black-box techniques machines will increasingly run algorithms that are beyond the comprehension of human agents. Whilst we acknowledge that historically machines could not have been accorded intentionality (Pickering, 1993), we question whether that is beginning to change. Given advanced programming techniques where the goal is determined by organic agents but the means and methods of achievement are left to automated intelligence we may perhaps be getting closer than ever to moving from a semiotic notions of material agency to something more complex (Berente *et al.*, 2021). We acknowledge however, that this is an area that requires significant further research.

The foregoing highlights in keeping with Teodorescu et al (2021) Jingyu et al (2021), Lebovitz et al (2021), Sturm et al (2021) that a major challenge facing organisational leaders, is where to deploy technology to greatest effect:

> "Organizational decision-makers are confronting this exploding discourse of the promises of ML-based AI and face decisions about whether and how to incorporate such tools in their organization' (Lebovitz *et al.*, 2021, P.1502).

As a consequence we see multiple instances of organisations failing to capture the expected benefit of their automation strategies – as exemplified by Lebovitz et al who evaluated five different ML based AI tools and found that 'none of them met expectations' (Lebovitz *et al.*, 2021, P.1501). Yet, outside of advisory firms, little practical guidance exists to support leaders to determine where to deploy technology to greatest effect. We seek to redress that balance.

5.5 Summary of Discussion

In Section 3.3, we highlight a number of perceived anomalies which we seek to explore through our work. In Section 4.7, we have summarised our results. In Table 14 below set out a summary of our resultant discussion.

Perceived Anomaly	Our Findings
Given acknowledged limitations of human agents, agency related concerns and the seemingly increasing viability of inorganic alternatives – it is somewhat surprising and even counterintuitive that there continues to be such significant emphasis given to human decision making in large organisations.	We find that automation fuels decision making - acknowledging two key variables impacting scope and scale of adoption. Data volume and complexity together with data sufficiency i.e., the extent to which data alone is sufficient to inform decisions, materially impacts the extent to which automation is deployed as both a coping mechanism and pioneer. We find that despite acknowledged limitations, human judgement and experience remain highly prized in relation to high-stakes organisational decision making. Agents are able to creatively project and anticipate the future in a way that can result in non-linear business benefits. The ability to navigate human to human interaction is a uniquely organic trait. We find a large number of instances where neither humans nor machines are perfectly suited to making decisions. In such instances human agents may be augmented by machines. The lack of general artificial intelligence and the inability of machines to transcend decision making contexts can result in a proliferation of pilots and paralysis.
	We find strong evidence across a range of industries that the increased deployment of connected devices and digital operations is increasingly

Perceived Anomaly	Our Findings
The exponential increase in connected devices, increasingly digital nature of organisations, and machine learning look set to result in machines that are increasingly *in the world* and well adapted to supporting complex decision making. Given the prevalence of the same in certain industries it is perhaps surprising that there appears to be somewhat of a lag across other large organisations.	reducing the physical world to bits and bytes. This exponential increase in data, coupled with machine learning, results in machines that are increasingly *in the world*. It can be argued that machines are increasingly adapted to responding to such complexity, overcoming traditional epistemological defences. In worlds that are increasingly translated into vast data sets – machines are potentially better adapted than humans to serving as coping pioneers. We find strong evidence that automation maturity differs by industry and function. Industries have access to large amounts of structured and semi-structured data are leading the charge e.g., financial services. Organisations slightly behind these leaders are characterised by smaller, less structured data sets - but where machines can help to solve high-cost problems e.g., mining companies. Whilst so called 'laggards'[228] have yet to establish an effective data strategy as result of largely physical operations e.g., airlines.

[228] Advisory (TM)

Perceived Anomaly	Our Findings
Technology appears to increasingly displace, reducing accommodation and resistance from directly impacted agents. Legislation, professional bodies, and customer preferences appear to be having a significant impact on deployment of technology.	We find evidence that organisational leaders are increasingly conscious of the impact of legislation (as exemplified by the EU Artificial Intelligence Act), consumer preferences, regulatory practice, and professional practice as sources of both accommodation and resistance. In parallel we find that the traditional of mangle of practice is moving further up the organisational hierarchy – with closed loop systems resulting in displacement rather than augmentation.

Table 14: Summary of Discussion

5.6 Proposed Model

Given that our work was motivated by an observation that the literature failed to assist leaders to determine where and to what extent to deploy technology in support of organisational decision-making, we use our results to develop a model for practice as set out in Figure 1 below.[229]

[229] Note: the graphical model depicted here was updated from the initial version highlighted in Appendix IV based on feedback gained from the feedback workshop described within this paper.

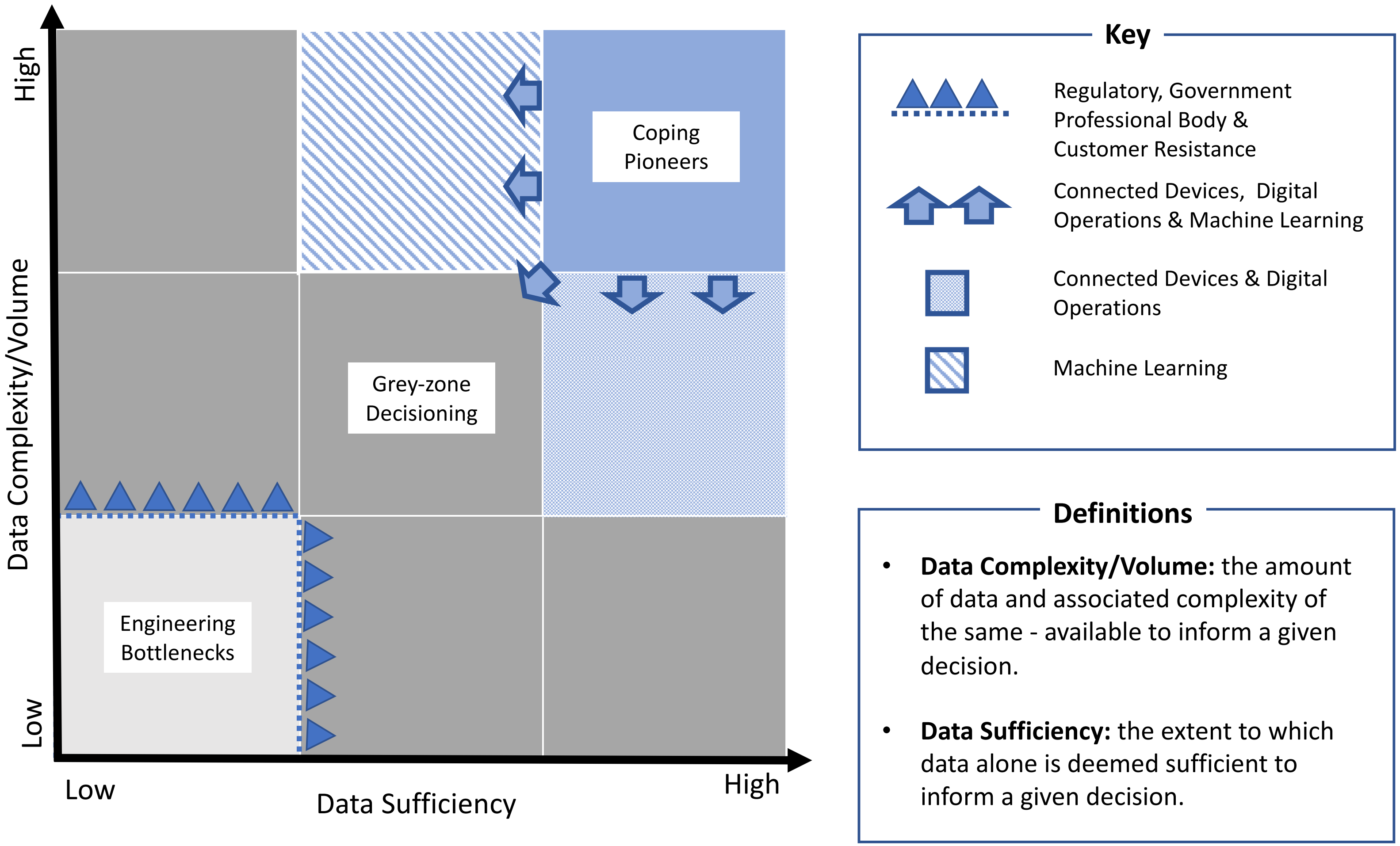


Figure 1 - A Model for Practice

The first of our reported aggregate dimensions acknowledges that data fuels the automation of decision making. Additionally, we acknowledge that such data sets are increasingly comprised of structured, semi-structured and unstructured data creating a multi-faceted challenge of coping with both volume and complexity. This phenomenon is represented in the model by our y-axis.

Again, predicated on the first of our aggregate dimensions, our model identifies accelerants in the form of connected devices, digital operations and machine learning which stand to materially disrupt automated decision making over time. This is represented in the top right of our model.

The second of our aggregate dimensions acknowledges that human judgement and experience continues to be prized in relation to high-stakes decision making. Consequently, our model recognises that not all organisational decisions can be made by reliance on data alone. Our x-axis reflects the fact that organisational decisions exist on a spectrum. At one extreme we find highly formulaic decisions that are suited to rational algorithmic decision making, whilst at the other extreme we find decisions that recognise the need for creative projections of the future and/or call for human to human interaction.

Finally, we reflect the third of our aggregate dimensions, that a combination of government, professional bodies, and customers will impact the pace, breadth, and scope of automation. This is represented in the bottom right of our graphical representation.

Our model highlights three decision zones. Which we set out in detail subsequently.

5.7 Post-Model Summary

We highlight in Table 15 below, the express connection between our proposed model for practice and our findings.

Key Findings	**Model Representation**
• Data is increasingly exponentially, driven by connected devices and increasingly digital operations. • Data becoming increasingly complex as a result of structured, unstructured	• Our y-axis highlights that data volume and complexity exists on a spectrum. • Our model acknowledges accelerators in the form of connected

Key Findings	Model Representation
and semi-structured data being generated and collected.	devices and digital operations – impacting where decisions may sit on the y-axis.
• Recognition that data alone is insufficient to inform certain organisational decisions. • Increasingly closed loop systems in high maturity processes.	• Our x-axis highlights that decision making exists on a spectrum. On one extreme decisions are highly rational and data driven, whilst on the other, decisions call for greater degrees of human judgment.
• Human agents struggle, unaided, to process and derive insights from data at high volumes. • Machines able to pioneer new insights from data. • Machines tireless and impartial – serve as coping mechanisms.	• These factors result in organisations looking to machines to serve as coping pioneers where data sufficiency and volume/complexity is high. This is represented within our model by the Coping Pioneer Zone.
• Recognition of a large number of decisions making domains where neither machines nor human agents are ideally suited in isolation – requires hybrid approach. • In absence of generic AI, narrow use cases can result in pilot proliferation and paralysis.	• These factors may result in organisations deploying a combination of automation and human judgement. This is represented within our model by the Grey-zone.
• Judgement and experience high-prized in relation to capital allocation decisions and other high-stakes organisational decisions.	• These factors are represented in our model by the Engineering Bottleneck decision zone – acknowledging that human judgement and experience

Key Findings	Model Representation
• Future is difficult to predict regardless of data quality and volume. • Human ability to creatively project the future can result in non-linear, exponential outcomes.	continues to be prized in relation to high-stakes organisational decisions.
• Deployment of technology in highly regulated industries seeing increasing focus from regulators regarding black-box techniques and machine learning. • Professional bodies in certain professions impacting deployment of technology. • Customer preference and habits impacting organisational decisions regarding technology deployment – but recognition that generational attitudes differ significantly. • Legislation increasingly impacting organisational decisions about technology deployment – offering both accommodation and resistance. • Trust and explainability likely to have significant impact on future deployment and use of technology.	• These findings are represented in our model by the accommodation and resistance that is expressly acknowledged in the bottom left, alongside our Engineering Bottleneck decision zone.

Table 15: Post-Model Summary

We have refined our model through feedback from leaders at two of the world's largest advisory firms. Before moving on to discuss our model in detail in Chapter 7, we recount the feedback received and the modifications made to our early representations of the model.

Chapter 6: Feedback Workshop

6.1 Introduction

As per Section 3.24, we held a feedback workshop with the Chief Data Scientist at Accenture and the Partner for Emerging Technology at Ernst & Young in order to present our findings and proposed model. We received apologies from a partner at McKinsey and ran the workshop with the two available participants. The resultant transcript can be found in Appendix V. The purpose of the workshop was to assess the utility and impact of our work and in particular our proposed model for practice. A number of interesting insights and outcomes emerged from the rich discussion that took place. The outcomes are set out below and have been used to refine the model for practice that follows in Chapter 7 of this paper.

6.2 Considered Use of Analogies

As highlighted previously, one of the CEOs we interviewed had described data as the new 'oil' – stating:

> "The data industry has just burgeoned and is similar to the early days of oil. I quite often say that it's a lot like oil because it's coming out of the ground raw. It's not of use to anybody – but once it's been processed it can be incredibly valuable." C-suite – CEO (RH)

It was not an analogy we had come across previously and it resonated strongly and appeared to have strong explanatory power. Consequently, we have reported it in our findings and highlighted the same during our workshop presentation. It drew an interesting reaction and was the first thing highlighted during discussion. Several issues were identified. Firstly, the negative associations with oil and the impact on the climate were flagged as something to consider:

> "Careful with the oil analogy, be very careful. Just be super careful. I'm sure Simon agrees. Use electricity. It's easier. Nobody's gonna grumble. Nobody's gonna shout at you. No bleeding hearts are gonna scream at you." Chief Data Scientist - Accenture

This point was corroborated by both participants. We had not considered the environmental and political connotations associated with the analogy and the impact it would have on the intended audience. Useful feedback that could otherwise have derailed a discussion with a less friendly group.

It was also suggested that aside from the negative connotations associated with oil – it was a 'lazy analogy.'[230] Oil it was proffered, is quite straight forward – it naturally occurs, is extracted, refined and is relatively easy to move. It was suggested that electricity is a more fitting analogy given its complexity and the challenges associated with the myriad of ways that it can be manufactured, stored, and consumed:

> "And the truth is that it's a better analogy - because it's something we manufacture versus oil, which is something we don't manufacture, we extract, right… How we distribute electricity, how messy it is. It's all over the place. All the layers that you gotta deal with to store it, and then it's more akin to the problem of the data in an average company than oil, which is actually quite simple, you pump it out, you shove it over there, you refine it and you send it to the shop." Chief Data Scientist - Accenture

Whilst we take on board the feedback and acknowledge electricity as a useful analogy – we believe the two analogies are intended to make subtly different points. Oil was used, in the context of the original discussion in which it was highlighted, to suggest that data in its raw form has limited value – but is transformed once refined. The point being expressed by the electricity analogy is more orientated towards the complexity of data. As is the case with electricity, data can be created in a myriad of ways, is difficult to manage – but has a raft of applications once mastered. We suggest that both analogies have a place – however, we will certainly be considered in our use of the former in organisational settings and have modified our presentation materials accordingly.

6.3 Value of Data

It was highlighted that our proposed model for practice did not take account of the value of data:

> "Another interesting thing to think about is value, the molecular value of data. It is not the same. The value of a piece of information about Simon or myself or you buying some gasoline in the BP gas station over there has effectively a minute amount of value as an electron of data, right, versus the same size of data at GCHQ – which is massively important because it can lead to a terrorist attack. So, there is the idea that not all data has the same value to all people and

[230] Chief Data Scientist - Accenture

> the way I tend to talk about it is - if you read Harari's philosophy – he says that the value of data is the question of our time." Chief Data Scientist - Accenture

This point was expanded subsequently to address the notion that the value of data is dynamic over time. The assertion being that not only is data not all of equivalent value – but equally that certain data has a shelf life. An example highlighted was that the recent pandemic had rendered certain historical data sets less valuable than they had been previously. Given that the world looks fundamentally different as we have emerged, historical data sets do not necessarily help us to anticipate future patterns.

We fundamentally agree with the points raised. That said, our model is not intended to address the value of data. Data clearly plays a critical part in our model given that we have highlighted that data fuels the automation of decision making. However, we steer clear of the value of the associated decisions and the value of the data itself. Intuitively decisions made within our Engineering Bottleneck zone will be of greater import than those in the Grey-zone – but the observation is not material to the application of the model. As observed, 'in your nice model, you act in different ways, if money is no object. At GCHQ, you must get all data – because no matter how small the data is and no matter how scarce it is in your model, I don't care if it's just one tweet.' The reality is that the observation is critical to determining one's data strategy and this is highlighted in the considerations sections of our model – but representing data value in the graphical representation of the model itself reduces the simplicity and explanatory power. We have however drawn this point out more clearly in the considerations section of each of our three decision zones.

6.4 Creativity & Judgement

We have highlighted that a key engineering bottleneck concerns the fact that humans are able to achieve exponential outcomes by predicting or anticipating the future. We have suggested that there is a creative, non-linear element to this trait which is difficult for machines to replicate. This point clearly resonated strongly 'the other note I made is you've said that machines will not give us creativity. Double down on that. Machines are not gonna do creativity.'[231] A useful endorsement of one of our primary themes.

However, it was then observed that machines weren't capable of judgement 'but it connects to your point on judgement, which is another absolute truth, which is that machines can inform

[231] Chief Data Scientist - Accenture

judgement. They cannot replace judgement.'[232] This subsequent point requires more careful consideration. The reality is that this statement is not strictly accurate - depending on the nature of the judgement being made. This point was subsequently acknowledged, 'except in places like you describe - in things which are very transactional. The factors are very easy to explain.' Whilst one of the core principles of our model is that judgement and experience continue to be prized in relation to high-stakes decision making – it should be deployed with care and in appropriate circumstances. It is not accurate to state that machines are incapable of replacing human judgement without carefully unpacking that statement and the associated context. Certain decisions, such as credit risk in financial services, which would historically been considered as requiring human judgement, are now considered to be perfectly suited, in the vast majority of instances, to being made by machines.

6.5 Quality & Feedback Loops

The foregoing discussion on judgement was subsequently extended to touch upon the quality of decision making:

> "So, the point you're making now - I would just build on around the concept of the evaluation of the quality of the decision, right. So, your model doesn't reflect the quality of the decision. So, was it the right decision or not?" Partner for Emerging Technology - Ernst & Young

A fair challenge. Our model is silent on quality – with the unstated assumption being that if the model is applied appropriately with corresponding technology – the decisions will be optimal. In the Coping Pioneer zone – decisions will be economically rational. By contrast, decisions made within the Engineering Bottleneck zone will be more subjective and based on experience and judgement. In practice one would expect feedback loops to determine whether a given decision should continue to reside in a particular decision zone – based in part on the quality of decisions being made and in part by the dynamic factors we have highlighted.

The pleasing aspect of this element of the discussion was twofold. Firstly, the seamless adoption by the participants of our descriptors during the discussion – which reflected those in our proposed model – and the second being an acknowledgement that the proposed model was not static:

[232] Chief Data Scientist - Accenture

> “What are the implications of saying that for your model? Well, the implications of that are there's some sort of feedback loop - you know. You talked about this notion of the model not being static. There's some sort of feedback loop in all of that, so if you look at the coping pioneers, if you look at the credit decision right. You know, Fernando you will have been involved in projects with clients over the last five years. Probably a bit longer in this space. We saw a massive take off in this particular space - when the banks were getting, the UK banks in particular, were getting turned over by the government for miss-selling of credit products, right. And there's been about three different waves of that and it just was impossible. They couldn't deal with it without doing exactly what you've said. It really was true that this was about 5 to 7 or 8 years ago now it really embedded the use of the tools you're talking about. Even in those banks that were initially a little bit resistant.
>
> But the point is - as that work from seven or eight years ago evolved. It got better and better and better because people learned about the quality of the decisions they were making. And the coping pioneer of your model, the outer arc, moved further down as a result of what was possible. So, there is something about the quality of decisions that shifts and advances the arcs in your model. I think that's worth talking about.” Partner for Emerging Technology - Ernst & Young

Within our over-arching narrative is the notion that the model constantly be revisited by organisations given that dynamic factors are in force. We will ensure that this point is sufficiently emphasised as it is a critical component of the model and one that differentiates it from the somewhat static models that exist today.

6.6 Change Management, Trust & Ethics

A central point of the discussion evolved around change management – perhaps unsurprising given the nature of the participants roles:

> “Now another one I had is. I think you've covered it. But it's always a problem of change more than it is a problem with technology - because the technology wick has been lit. It's a wildfire. So, you don't have to worry about the technology happening – it’s going bonkers.” Chief Data Scientist - Accenture

This point speaks to implementation – with the observation being that change is as much about people as it is about technology. We concur with this observation, and it was borne out through our research.

The critical role of 'trust' was highlighted and interestingly the notion of vestigial behaviour. Again, favouring an analogy, the comparison was drawn between a manual and an automatic car – and the vestigial habit of reaching for a non-existent clutch – borne out of habit and the safety critical nature of the device. This point was confirmed and built on through discussion, with the observation being made that organisations gradually came to trust technology over time. The example of the early days of ERP systems was cited – where data sets and processes were initially questioned. Over time leaders have become more comfortable based on outcomes and continual refinement. This issue, however, continues to be an important topic given that: 'imagine in a corporate environment where all your safety mechanisms - the things that tell you that you're gonna be okay. The things that tell you that you're not going to get fired. The things that tell you that everything is fine. They're all vestigial behaviours.'[233]

The conversation then shifted to discussion about government intervention in light of equivalent concerns around trust and macro social-political factors:

> "societal equity questions around this – that governments feel they need to weigh in on, industry regulators feel they need to weigh in on, companies themselves, feel the need to weigh in on because it undermines their ability to use technology." Partner for Emerging Technology - Ernst & Young

Both participants went on to highlight that they have recently introduced policies related to the governance and management of automated decision making. Interestingly Ernst & Young's policy is only a month old - but they highlighted that it was highly topical for other large corporates with the likes of General Motors actively seeking advice and guidance in relation to the same. This has seemingly become an increasingly material governance issue in very recent times:

> "I can't deliver anything without going through the AI ethics board. Nothing. Zero. I can't do it. And they don't try to stop me because they don't trust me - but because there's such a weight of vestigial behavior coming behind me - that without malice, it overrides all of the things that we need this technology to do

[233] Chief Data Scientist - Accenture

> and trust and work with. We need to create new behaviors, right." Chief Data Scientist - Accenture

Interestingly, neither participant suggested that this should ultimately stop the use of technology. In keeping with Sampson (2020), both highlighted the fact that decisions made by humans are imperfect – extending the driving analogy to suggest that none of us are perfect drivers and a little automated help should be welcomed. The same by extension should be true in business.

This element of the discussion was particularly interesting – given the nature of accommodation and resistance that we have highlighted in our model. The discussion flagged both elements. AI ethics committees will both legitimise practice and adoption whilst curbing and inhibiting usage outside of defined parameters. It was highlighted that micro dissatisfaction with decisions (in this instance the example cited was an individual's reaction to a credit decision) should not inhibit the direction of automation:

> "That's the micro customer response, but at the board level they need to deal with the macro impact of those decisions and not get dragged into if you like pushing or shrinking the pioneer arc that you have - because there is a sense that the human decision-making process, for all of its qualities of creativity etcetera, etcetera, wasn't perfect in the first place." Partner for Emerging Technology - Ernst & Young

This dialectic is important, and it is interesting that over the course of our studies this has moved quickly from being a theoretical consideration to a practical governance mechanism that is being actively implemented. Again, whilst there may be an issue of emphasis to consider, the discussion affirmed a key element of our model.

6.7 Houston, We Have a Problem

Not altogether unexpectedly, given the nature of our participants, they did identify a challenge with the graphical representation of our model - highlighting an issue with the way that the Coping Pioneer decision zone was graphically represented:

> "There's a slight problem with your model. The picture of the model, not the model itself – which is totally fine. It is the picture, which is that if you look, if you look at the axis, you've got right, you've got the complexity and volume, which is totally fine, and the data sufficiency. The bottom right is a place where

machines do very badly. Really badly. Very small amounts of data - bad." Chief Data Scientist - Accenture

In the original graphical representation of the model – the Coping Pioneer zone did indeed extend to high data volume/complexity and low data sufficiency scenarios – and on the corresponding extreme to high data sufficiency and low data volume/complexity scenarios. We acknowledge the issue with this unintended representation – as highlighted in Figure 2 below, in which the deficient areas are captured in red.

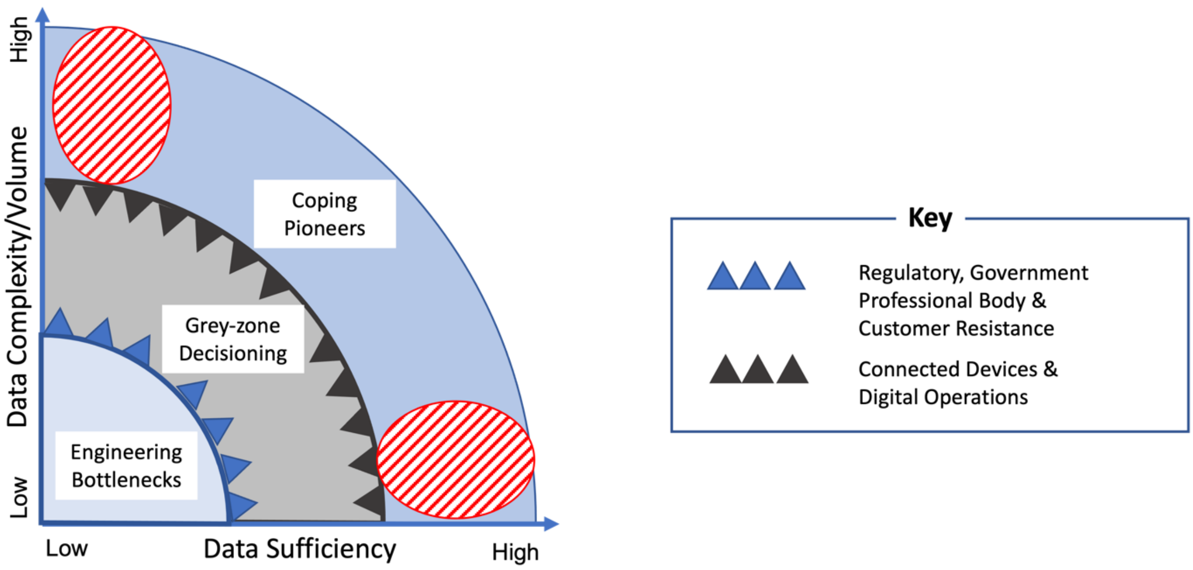


Figure 2 - Initial Model Deficiencies

Data has to be sufficient to enable decisions – in other words there has to be enough of the right sorts of data. As such this could be addressed via a simple footnote – as suggested by the participant. However, the comments prompted us to review the model and identified further challenges with the way the model was represented graphically. A similar issue applies to situations where data complexity is high and data sufficiency is low. Such instances are not well suited to either human or machine in isolation. The natural consequence is that it becomes an extension of our Grey-zone. Take for example identification of bias in the hiring process – an issue identified by one of our interviewees[234]. There is a significant volume of data in the form of CVs, interview notes and subsequent hiring decisions – but does an algorithm exist to identify the patterns and to recommend actions? The answer is, not yet. This point was highlighted in a recent paper by van den Broek et al

[234] C-suite – HR (JC)

> "We found that the grand goal of developing knowledge independent of domain experts does not hold when ML is used to transcend complex knowledge work, such as in the case of candidate selection" (van den Broek *et al.*, 2021, P.1573).

Thus, it would firmly sit within the Grey-zone – but with the potential to be automated in the future.

Equally upon further reflection, we consider that situations where data complexity is high, but sufficiency is modest to be instances where machine learning will potentially serve to accelerate automation in the future. As in the instance of bias in hiring decisions – data sufficiency could be increased with appropriate algorithms. At the other extreme, where data sufficiency is potentially high but there is inadequate data – connected devices and digital operations will serve to accelerate. Take for example wearable devices that were highlighted during our interviews.[235] The resultant data will transform the way we think about healthcare resulting in increasingly closed worlds where doctors no longer have to ask for basic lifestyle information to inform diagnostics. Neither of the foregoing points change the fundamentals of our model – but they do add nuance and depth.

To reflect the foregoing, we have amended the graphical representation of the model as set out in Figure 3 below.

[235] C-suite – CIO (GC)

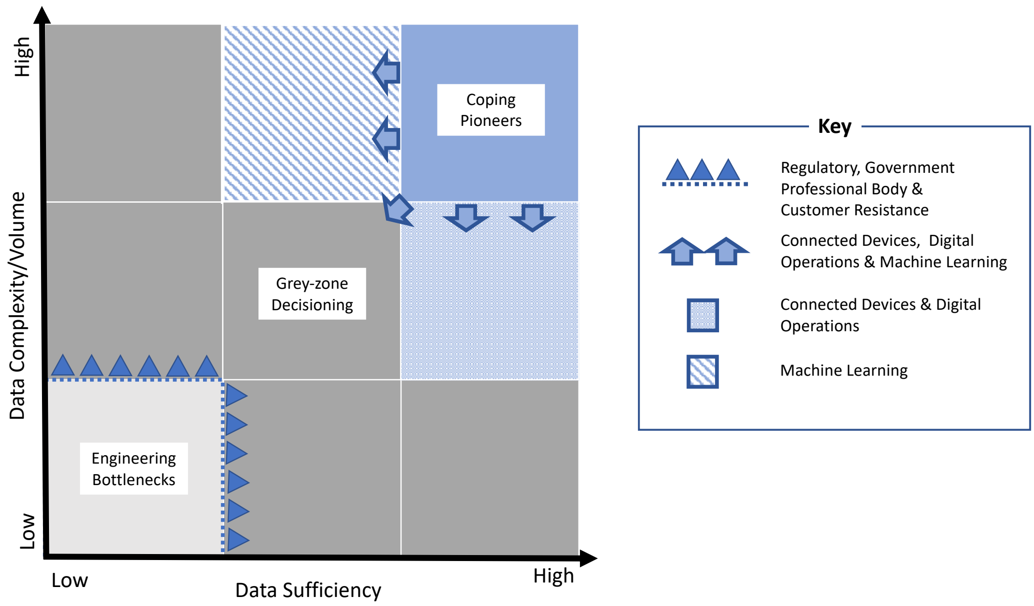


Figure 3 - A Revised Model for Practice

The modifications above do not change the fundamentals of the model itself – all of which continue to be relevant. The feedback usefully highlights that grey-zone decision making is both literally and figuratively pervasive at present. The accelerators will however continue to impact the reduction of the now expanded Grey-zone over time.

6.8 Practical Application

The discussion highlighted that our research area continues to be highly topical. Examples cited from financial services, GCHQ and telecoms together with practical examples of ethics committees only reinforcing the fact that the discussion is getting increasing amounts of airtime among senior leaders. Various references were made to board level discussions on the topic – with the point being made that board *literacy* on the topic is perhaps lower than we might anticipate and thus simplification and analogy are necessary in what is increasingly a senior level, critical debate.

In response to the question posed regarding the utility of our proposed model – both agreed that it would have practical application:

> "I can tell you that I can send you 5 models like this that we use for consulting – focusing on strategy. They are very, very similar. And by the way, I don't mind sending them to you. They come at it from a deeper perspective in terms

> of the industry they work in – so they are not as generic. Your model is definitely useful – there is no doubt about it.” Chief Data Scientist - Accenture

The model can easily be applied to specific contexts (see Section 7.7) – and as such we take the foregoing as a positive endorsement of the model’s broad application. The foregoing was reinforced by:

> “Yeah, yeah, look, I mean, I think the model is useful. It has to be because we've just had a very clear discussion based around it. That hasn't challenged the fundamental premise on which it's built, right. So, our discussion has been additive and explorative rather than questioning the fundamentals.” Partner for Emerging Technology - Ernst & Young

Given that the stated aim of the model was to generate discussion and not to provide definitive answers we consider this to be a material endorsement. Additionally, given the level of expertise and experience of our participants – the fact that it was sufficient to engage and stimulate not only discussion, but suggestion for improvement, refinement and expansion were also significant outcomes.

Some months prior to the workshop we had the opportunity to meet with one of our original interviewees during an ad hoc meeting. They expressed an interest in our progress and we had an impromptu discussion on the subject. In the absence of a whiteboard, we had drawn a crude outline of the model on a small piece of paper. See Figure 4 below.

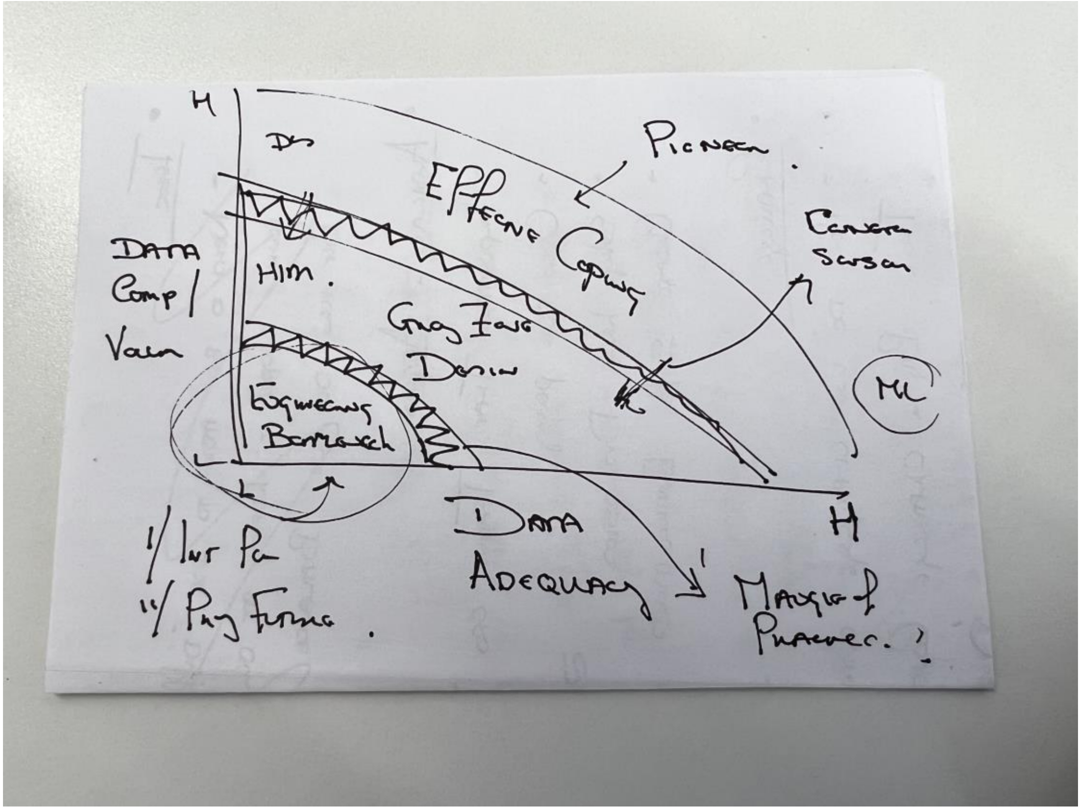


Figure 4 - Back of a Napkin

In a similar manner to the workshop, we had a rich discussion. At the time we were somewhat apologetic about the simplistic nature of the model. Unprompted we received an email subsequently that stated:

> "To be able to summarise a hugely complex topic on the back of an envelope in the way you did is, in my book, a measure of your command of the topic. So never feel the need to apologise for over-simplifying." Board Advisor (SR)

This theme was reiterated during the workshop with the comment being made that 'look, you know, like all great things, its' simplicity is powerful. And you know, you can take this into a board discussion, right? And they'll get.'[236] This final point is a significant, positive endorsement of the real-world impact of the model.

On the back of the foregoing there was a clear recommendation that the final slide that we had shared be revisited:

> "I do think the dimensions that we've all discussed this morning are really important to acknowledge because they drive the movement in the model and

[236] Partner for Emerging Technology - Ernst & Young

> movement is powerful. As you say it's a dynamic model and being able to expand on the dynamism and what drives it is as useful as being able to show the categorization that it gives you.
>
> I also think the last slide I was reading last night about implications for practice I think - I think those probably need another scrub through in the context of the type of discussion that we're having now. You could get even more pointy and specific about them." Partner for Emerging Technology - Ernst & Young

Again, this felt like a very positive acknowledgement of the real-world application of the model and associated impact, which was considered to be somewhat understated, and which we have subsequently adjusted and also reinforced in our conclusions herein.

6.9 Summary

It is always daunting to present the outcome of one's work and even more so when the recipients are acknowledged experts in their field. That said, notwithstanding the foregoing, the resultant dialogue was invaluable. From relatively modest, but highly impactful observations, regarding the use of analogies through to material observations on the graphical representation of the model – the discussion added to and built upon the core themes of our research.

What was clear from the discussion and observations raised is that the topic is highly engaging and relevant to practitioners. What was equally clear is that our contribution has highly practical applications – that extends to the board level. Whilst we have adapted certain elements of our model based on feedback – we were delighted with the way the model was received, even to the point of the participants adopting our use of language. The discussion also served to remind us that the model will continue to evolve and adapt as it is deployed in practice and with the feedback from others. We must, as ever, be considered in the feedback that we adopt – but we believe with careful maintenance our model will remain relevant in the highly dynamic future organisations are moving towards at pace.

Chapter 7: A Model for Practice

7.1 Introduction

We were motivated to undertake this study based on our perception that automation would have a material impact on the future of decision making in large organisations and that the area was underserved by academia. We suggested that the knowledge, attitudes, and practices of senior leaders would have a material impact on the scope and breadth of future automation. We go on here to explore the practical implications of our findings for organisational practitioners and leaders.

It is clear from the work we have undertaken that at all levels of the organisation there is growing expectation that decisions will be increasingly data driven. Given the reduced cost of technology, organisations are looking towards automated solutions to drive efficiency, reduce cost and exploit the opportunities presented by data. Whilst human judgement and expertise will continue to be valued, we can reasonably expect that the number of instances in which such judgement is deployed to reduce over time and to be augmented by data where reasonably practicable. Moving forward we see the trend for the increased deployment of sensors and connected devices, coupled with machine learning, to support the continued encroachment of machines. This encroachment is however likely to be held in check and curbed by narrow use cases, defensive positions from regulators, professional bodies, and governments, together with resistance from certain customer segments.

Our research suggests that different industries and functions are at different stages in the adoption curve.[237] One advisory partner noted that organisations that have access to large amounts of structured and semi-structured data are leading the charge. Financial services falls neatly into this category and we noted the advanced use of automated decision making in credit decisions.[238] Highly structured, increasingly closed loop systems are deployed where rational decisions can be well facilitated through algorithmic, impartial responses – serving to 'cope with the scale, size and complexity'[239] of the associated data. Organisations slightly behind these leaders are characterised by smaller, less structured data sets - but where machines can help to solve high-cost problems. We noted mining companies in this category. Finally, the so

[237] Advisory (TM)
[238] C-suite – CIO (GC), C-suite – Risk (CO), Partner (SC), Partner (TM), Service Provider (MoK), Service Provider (RP)
[239] Advisory (TM)

called 'laggards'[240] have yet to consolidate or collect data as a result of the nature of their physical operations – we highlighted the airline industry as an example of this.

Not only do industries differ in their adoption of technology – but we also see different enabling or support functions moving at differing speed. Finance leaders are typically looking to embrace technology to reduce the manual effort associated with highly repetitive, structured procedures. Leaders demonstrated a heavy focus on meeting industry benchmarks in relation to both costs and efficiency – although we note that there was scepticism about ever achieving a so called 'lights out' function[241]. One leader we spoke to described finance as representing 'machine intelligence'[242] and thus it should perhaps not come as a surprise that such an analytical, rational decisioning unit should be a focus of automation efforts. We also saw evidence that elements of human resources are beginning to accelerate as teams look to reduce bias and promote diversity through use of automation in talent acquisition[243] - in keeping with Charlwood & Guenole who found that:

> "a recent industry study found 300 plus human resources (HR) technology start-ups developing AI tools and products for HR or people management, with around 60 of these companies 'gaining traction' in terms of customers and venture capital funding" (Charlwood & Guenole, 2022, P.2).

Legal functions, a stalwart of the traditional professions are also not immune, with leaders highlighting that disruptive start-ups are challenging the manner in which legal discovery and support is provided to organisations. We also noted that marketing and media are making use of machines to target audiences with greater accuracy. Thus, whilst the pace and breadth of adoption may differ by function there are few areas of large organisations that are not looking to accelerate automated decision making.

Notwithstanding the foregoing our discussions suggested that machines are currently limited in their application and scope. In the absence of the 'holy grail of generic AI'[244] – machines must be developed to address relatively narrow use cases. In other words, because machines lack the ability to move seamlessly between contexts – they must be built, adapted, and tailored for different use cases. This point was highlighted by Charlwood & Guenole who stated that 'a

[240] Advisory (TM)
[241] Partner (SC)
[242] Board Advisor (SR)
[243] C-suite – HR (JC), C-suite – Strategy (BM)
[244] Service Provider (FL)

complicating factor are 'edge-cases'; new scenarios with features that the AI has not encountered before so cannot initially classify' (Charlwood & Guenole, 2022, P.3). For organisations this can result in a number of challenges. The sheer volume of use cases – which can run into the thousands,[245] resulting in paralysis and a proliferation of pilots.[246] The more complex an organisation the more likely we are to potentially experience this phenomenon. Such proliferation calls for hard choices around return on investment and impact.[247] This may go some way to explain why financial services are so advanced – given that the majority of credit decisioning processes are highly repetitive and core to the business. By contrast airlines have a myriad of divergent business processes each of which would likely have to be optimised in turn. The consequence is that organisations require well thought through automation strategies that take account of the areas where they are likely to see the biggest returns in order to avoid pilot paralysis.

Building on our work we have created a model for practice – as set out in Figure 5 below.[248]

The model is intended to be used to assist organisational leaders to consider their automation, digital and talent strategies. In the sections below we use our three decision zones to set out the characteristics of decisions within each zone together with the suggested automation strategy and key considerations. We also highlight the role that accelerators and inhibitors will play in the future and that management will require a 'constant process of emergence and performity' (Berente *et al.*, 2021, P.1437). A core design feature of our model is ability to reflect a dynamic and rapidly evolving landscape.

[245] Service Provider (FL), Service Provider (KR), Service Provider (MoK)
[246] Advisory Partner (TM)
[247] Service Provider (FL)
[248] Note: the graphical model depicted here was updated from the initial version highlighted in Appendix IV based on feedback gained from the feedback workshop described within this paper.

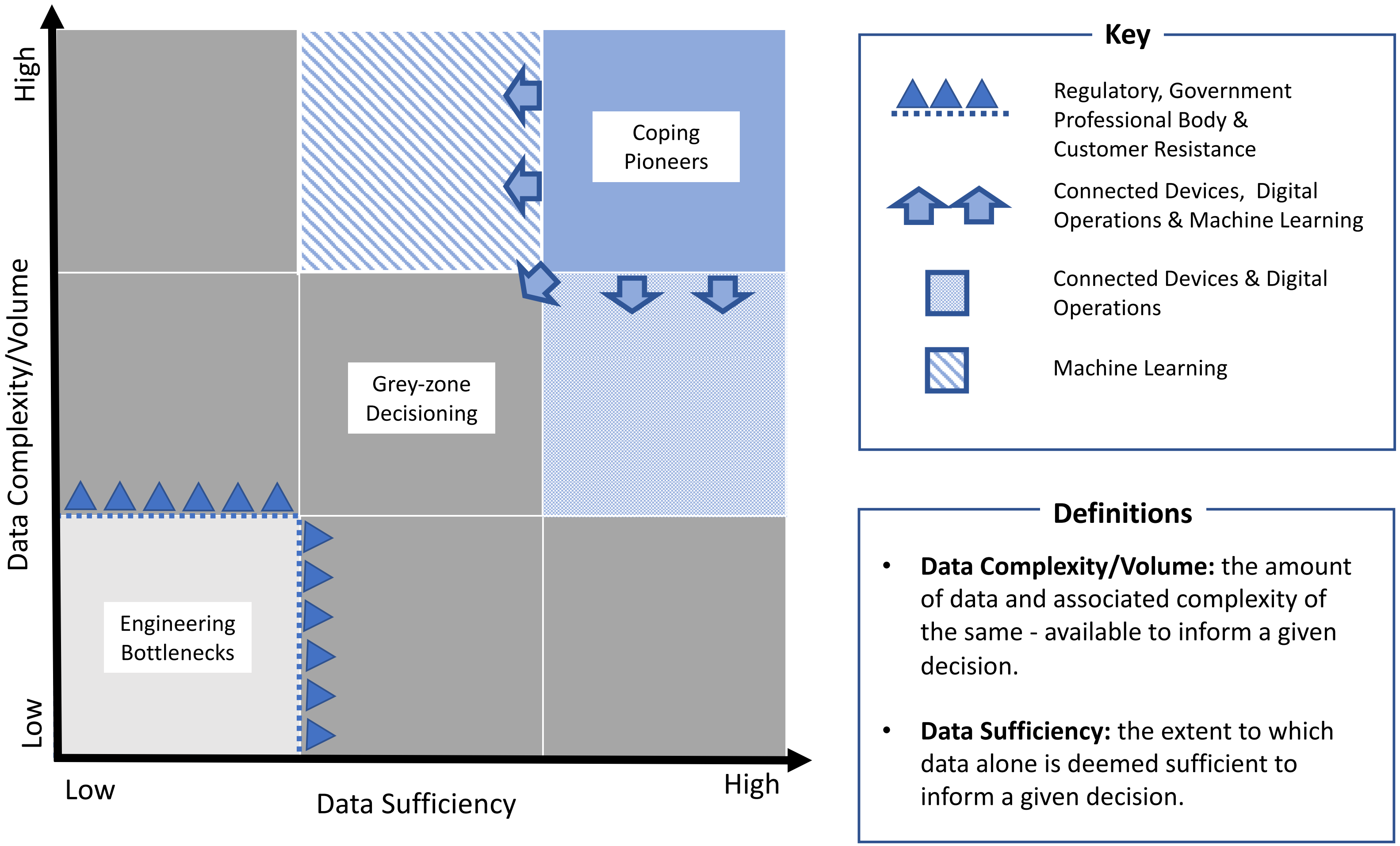


Figure 5 – A Model for Practice

7.2 Machines as Coping Pioneers

Our model highlights that where data is sufficient to drive decisions and available at significant scale – machines potentially serve as coping pioneers. Table 16 sets outs the characteristics, suggested automation strategy and considerations associated with this decision zone. Decisions in this zone are likely to be highly repeatable using hard decision logic – characterised by extreme volumes of structured, semi-structured and unstructured data. In such scenarios organisations should exploit automation to increase the efficiency of their operations, pioneer new uses of data that would be indiscernible to human agents and promote data democratisation.

In this decision zone – automation will likely result in displacement of human labour - although such capacity may be redeployed by the organisation. In order to extract full value from automation, machine learning may be necessary to deal with the complexity of the data landscape. As such, organisations will need to consider both resistance and accommodation from professional bodies, regulators, and customers. Failure to exploit automation to the maximum extent of such accommodation may result in organisations falling behind the competition. Where machine learning and algorithmic methods are deployed, explainability will likely be a material consideration and organisations should consider the extent to which an ethics committee is required to sit above such decisions.[249] Equally organisations need to pay close attention to their data strategy to guard against unintended machine bias. Automation in this zone can provide a competitive advantage for early adopters – but may be short lived. Laggards will be forced to follow quickly in order to compete – and the deployment of such technology will likely be an existential capability – as we have witnessed in the financial services industry.

Decision Zone Characteristics	Automation Strategy	Considerations
• Highly repeatable, hard decision processes at scale • High volumes of data (structured, semi-	• Machines deployed as coping strategy • Machines used to pioneer ways to exploit data	• Machine learning may be necessary to maximise value • Organisations should make conscious

[249] This point was highlighted in our Feedback Workshop. Both Accenture and EY have implemented ethics committees and are increasingly advising clients on the same.

Decision Zone Characteristics	Automation Strategy	Considerations
structured and unstructured)	• Data democracy enabled • Limit human decision making • Consider deployment of connected devices as part of data strategy	decisions about black-box technology • Consider establishing ethical board to oversee potential societal and reputational impacts • Customer, regulatory, government & professional body accommodation and resistance • Machines will displace human agents • Closed loop processes may enable zero touch or lights out processes • Competitive advantage if early adopter • Competitive necessity if fast follower • Robust data strategy required to collect and exploit data • Recognition that not all data is of equal value • Value of date may increase or diminish over time and is not static • Trust important in adoption of automation

Decision Zone Characteristics	Automation Strategy	Considerations
		– consider change management and vestigial behaviours
Decision Example: Credit decisions in financial services. Decisions are highly repeatable and largely data driven, closed loop processes. Whilst exceptions may apply – vast majority of decisions will be automated enabling organisation to cope with complexity.		

Table 16: Machines as Coping Mechanisms

7.3 Engineering Bottlenecks

At the other extreme of our model, we identify a decision zone characterised by engineering bottlenecks. Table 17 sets out characteristics, suggested automation strategy and considerations associated with this zone. The decision zone is characterised by low volumes of high-stakes decisions – typically the most important non-recurrent decisions made by organisations will reside in this space. Data to support such decisions will be modest and often subjective or intangible. Hard decision points will be used to inform decisions but will not be considered sufficient to drive decisioning. Decisions will require creative projections of the future – typically associated with capital allocation. Decisions requiring significant amounts of human-to-human interaction also reside in this decision zone. Machines may be used to inform hard decision points and to augment the information available to decision makers – but judgement and experience are likely to continue to be highly prized by organisations. These soft decisioning characteristics create natural engineering bottlenecks - limiting the extent to which automation can encroach. [250]

Organisations should approach this decision zone with caution. Human judgement in this space can serve as a significant competitive differentiator – enabling exponential outcomes. However, judgement is subjective, and soft decisioning processes are hard to articulate rationally. Consequently, organisations should take care to be aware of, and eliminate, bias and to consciously delineate between hard decisioning processes and intuition. Data asymmetry between the board and senior leadership will limit the formers' ability to fully validate the basis for decisions and requires significant degrees of trust. Given the high-stakes nature of the decisions involved – augmentation with known data points should be utilised wherever

[250] It should be noted that this may change in the future.

reasonably practicable. Decisions in this space are notoriously challenging – despite potential exponential impacts – corporate history is littered with examples of abject failure.

Decision Zone Characteristics	**Automation Strategy**	**Considerations**
• Low volumes of data – including semi-structured and unstructured data • Low volume, high-stakes decisioning • Decisions require either creative projection of future and/or human to human interaction to enable	• Machines deployed to augment human decisions • Human judgment highly prized – characterised by experts – invest in talent	• Need to be cognisant of bias • Decisions will be subjective and prone to error • Data asymmetry likely to exist between decision maker and both board and shareholders • Exponential business outcomes may be achieved • Human judgement may be a competitive differentiator • Talent strategy and effective governance critical
Decision Examples: Acquisition. High-stake capital allocation decision where projection of future state is required to inform decision. Decision is likely to involve significant judgement in the absence of hard data to support such decision.		

Table 17: Engineering Bottlenecks

7.4 Grey-zone Decision Making

Between our two extreme decision zones we identify grey-zone decision making – as set out in Table 18. Visually, this domain is currently the most dominant zone within our model and such representation adequately reflects current reality. With the exception of highly automated digital native organisations, the majority of organisational decisions are likely to reside in this decision zone. Decisions are likely to require a mix of hard data and processes together with elements of human judgement. Data is unlikely to be available to drive entirely hard, rational decisions and processes are likely to be very specific to given use cases. Where automation is introduced, it is likely to be against one or more of a large number of potential use cases. Consequently, payback and return on such automation may be limited and care must be taken to ensure appropriate prioritisation and to avoid pilot paralysis.

Automation in this decision zone is likely to see human agents in the middle. Whilst some displacement may occur – a number of experts will be required to continue to support the associated process. This will result in a local dialectic of accommodation and resistance. Organisations may face resistance from human agents and care must be taken to guard against unintended consequences. Significant change management effort is required to adequately support automation within this space.

Decision Zone Characteristics	**Automation Strategy**	**Considerations**
• Moderate levels of data – both structured, semi-structured and unstructured • Decisions require a mix of hard and soft decisioning processes • High volume of moderate value decision processes	• Use case specific automation – may involve partial automation of process • Focus on high impact processes • Consider use of connected devices • Consider use of machine learning	• Care should be taken to avoid automating processes without tangible return • Avoid pilot paralysis • Automation strategy may result in resistance • Machines will augment rather than displace – may result in human in the middle • Human agent resistance may be significant and result in dialectic of accommodation and resistance – consider change management approach

Decision Zone Characteristics	Automation Strategy	Considerations
		• Need to be cognisant of bias • Trust important in adoption of automation • Decisions will be subjective and prone to error • Avoid automating bad processes • Data asymmetry likely to exist between decision maker and owners
Decision Example: Business case for customer acquisition (e.g. sales proposal). Rational decisioning models will be used to calculate margin, cashflow and balance sheet – but will be heavily informed by input from human agents. Judgement required to determine sale price in competitive situations.		

Table 18: Grey-zone Decision Making

7.5 Accelerators

Organisations should be aware of technology that will accelerate automated decision making. The growth in the number of connected devices deployed by organisations will create new data sources for exploitation. As this data volume grows, machine learning will enable organisations to extract greater insight and drive automated decision making – where such data is sufficient to inform hard processes. Additionally, as organisations transform their operations to become increasingly digital – data will be generated, that again, with the right application of tooling can lead to greater automation. A robust data strategy is required to ensure that data is collected and stored in a manner to allow exploitation in due course. These accelerators will see machines increasingly encroach from the extreme of our model – with increased data leading to existential need to use automation to pioneer and cope with complexity. Organisations should consider where connected devices can be deployed to greatest effect and be prepared to move as fast followers where competition exploits.

As highlighted in our model where data sufficiency is high, but data volume/complexity is modest, connected devices and digital operations are likely to be strong accelerants. Whilst these characteristics result in grey-zone decision making – organisations should consider the extent to which investments to collect data will result in material benefit in the future. In such instances organisations should consider the extent to which data could and should be collected, the associated cost and resultant benefit. This area will likely be dynamic and rapidly evolve.

That said, all the data in the world will not help organisations to extract value without the ability to process and make sense of the same. Machine learning is likely to be critical in a number of instances to extracting value and pioneering insight. We have highlighted that where data sufficiency is currently modest, but volume and complexity is high – that machine learning can potentially be applied to good effect. The challenge in these instances will be to determine whether data sufficiency is modest because of limitations in analysing and learning from vast data sets which are beyond current capabilities. Untested assumptions should be avoided, and organisations would do well to regularly review and revalidate decisions made in this space.

As highlighted in our feedback workshop, not all data is of equal value. As such a key component in deciding where to invest in accelerators is assessing what data is likely to have the greatest return on investment. Decisions residing in our Coping Pioneer zone should almost certainly take priority on any automation roadmap – but beyond that careful prioritisation is required and that prioritisation should be both pragmatic and commercial. Ironically such decisions will often be made by human agents – requiring the ability to project and creatively anticipate the future.

7.6 Accommodation and Resistance

Engineering bottlenecks are likely to be protected through professional bodies, governments, and consumers. Organisational leaders need to pay close attention to changes in regulation. Whilst such legislation is typically associated with curbing behaviours – it should be noted that legislation will also set out the parameters within forms can operate legitimately. Progressively minded competitors are likely to exploit automation to the fullest extent permitted by such legislation. In a like manner customers and consumers will determine the boundaries of automated decision making – and should be expected to rapidly evolve going forward. Generational differences will impact the pace of change – but leaders should ensure that they are testing this dialectic on a regular basis. Again, progressive organisations will push boundaries in this regard and organisations should be prepared to act as fast followers or risk falling behind the automation curve. Effective change management will be critical in this regard.

7.7 A Diagnostic Tool

In addition to serving as a powerful communication device, our model for practice can be used in a practical way to support automation and digital strategies - serving as a diagnostic tool.

In order to illustrate how the model can be applied in practice we provide a crudely worked example based on the procurement discipline. A non-exhaustive list of decisions that reside within this space were identified and listed[251] - as set out in Appendix VI. These decisions and the data associated with each were then reviewed for volume/complexity and sufficiency. Figure 6 highlights these decisions once mapped within our model.

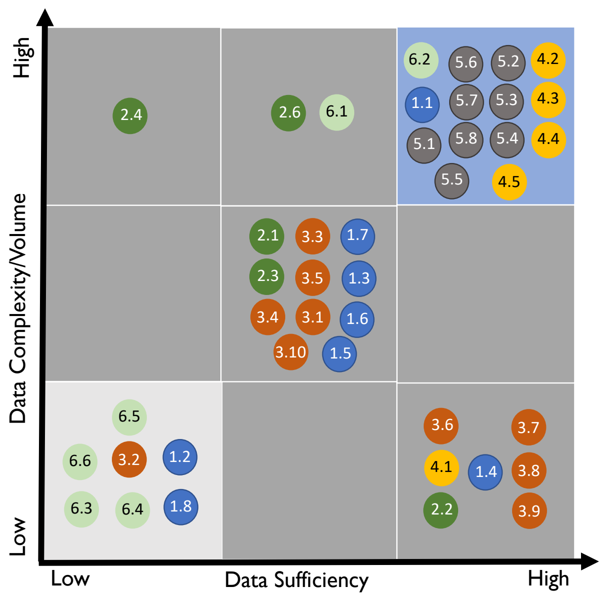


Figure 6 - Mapped Procurement Decisions

The resultant model suggests that procurement is an area that can potentially be well served by machines in the Coping Pioneer space. In the absence of an automated solution, tens of thousands of purchase orders and hundreds of thousands of invoices must be processed manually. However, automation enables automated workflow of approvals, automatic conversion of purchase requisitions to purchase orders and automated three-way match – enabling huge volumes to be processed without human intervention. This reduces the cost of

[251] Note for convenience we performed this exercise with a subset of our own teams – see Section 3.25.

servicing the organisation, reduces the risk of human error and fraud and creates vast data sets which can be analysed to identify opportunities to increase value and reduce cost. Given the efficiencies to be gained in this space it should be a key focus area. The implementation of such technology will displace human labour in the back office.

As would be expected, a number of decisions reside in the Grey-zone. Organisations should be careful to avoid investing significant amounts in solutions that may have questionable rates of return and potentially serve to complicate the overall system landscape. Decision 2.6 serves as a good example. Environmental, Social and Governance (ESG) is a key consideration for modern organisations – with issues such as modern slavery, diversity, equity, and inclusion, together with decarbonisation increasingly occupying board agendas.[252] Decarbonisation alone is a significant data challenge – with significant emissions sitting in Scope 3. The collection, review and actionable insight from such data could become either a competitive advantage or competitive necessity. It is a space that machines can potentially serve well. At present it is an area very much within the Grey-zone – with machines augmenting human talent. In the future however, with appropriate investment in automation it could readily move within the Coping Pioneer zone – leaving less room for subjectivity and closed loop systems that report emissions from source. It is a space that requires continual review as it is evolving rapidly.

The model also suggests that there are a number of areas that reside within our Engineering Bottlenecks zone. This suggests that for the foreseeable future the organisation will need to invest in human talent. A good example of the type of decision in this space – is the suppliers to be invited to respond to a tender. Whilst there are countless partners that operate in certain spaces – the decision as to whom to invite is ultimately based on organisational dynamics and judgement. It is impacted by relationships, perception of the importance of the account, diverse accreditation, and a raft of other subjective factors. It is a classic example of where human to human interaction plays a material role in the decision – with procurement leaders needing to balance powerful stakeholder interests and secure buy-in. Equally it requires projection of the future - particularly in relation to long term service-based deals where not only does a supplier's relevance today need to be taken account of – but equally important – the extent to which that relevance is likely to continue into the future.

[252] Note we report a discussion with a FTSE100 board member on this topic in our Contribution section of this report.

As highlighted previously, organisations can't consider their automation strategy in abstraction from the service providers that exist to support solutions. For the purposes of this illustration, we have used a system landscape produced by DPW (see Appendix VII) – one of the leading authorities on procurement automation solutions. The landscape map highlights the vendors and tools that exist to support procurement automation. These solutions can then be overlaid against the decisions in our model.

Decisions can be grouped to highlight where they can be served by the same solution. Figure 7 highlights solutions mapped against corresponding decisions.

Figure 7 - Solution Map

For the vast majority of organisations, it would not be practical to implement solutions across all of these areas at once and thus pragmatic and commercial prioritisation is required. Using the automation strategies and considerations that we have highlighted within our model for practice it is possible to review initiatives to determine investment priorities for the organisation – but we would suggest a heavy focus on the top right of our model.

One of the interesting things to note from the DPW automation landscape is the prominent role played by data and analytics. There are more solution providers highlighted here than in any other solution space. Again, this serves to reinforce how central data is to the automation of decision making. We also note that many of these analytics solutions are powered by machine learning and artificial intelligence. Understanding spend, which can range into the billions of dollars across hundreds of thousands of purchase orders, is a task that is beyond the most competent category managers – but is readily addressed by machines. Determining where to deploy such solutions will be key to organisations unlocking value and expanding the potential of machines to drive coping and pioneering insight.

As highlighted, our intention here is not to expand on every element of this worked example. We could write a dedicated thesis on this one enabling function alone. However, the purpose of including the foregoing is simply to highlight how our model for practice can be applied as a practical, diagnostic tool to inform both digital and human talent strategies.

7.8 Implications for Practice

Automation is set to fundamentally disrupt the way that organisations make decisions. In more advanced industries we are seeing this already. Financial services are increasingly commoditising their decisioning processes enabling them to use machines to cope with increasing demands and ever greater sources of data. At the same time back-office processes are becoming increasingly efficient using technology to support full population testing. The use of such automation drives significant efficiency reducing costs and increasing margins. Not only that but exploiting data through pioneering new ways to drive value creates new revenue streams. Such advances have to some degree been born out of necessity with the industry as a whole being disrupted by so called fintechs. Consequently, automation has become an existential capability for many organisations. As highlighted by Berente et al, 'given the current pace of investment in AI worldwide, managers will not have decades or centuries to catch up' (Berente *et al.*, 2021, P.1445).

Whilst not all industries are as advanced as financial services – all industries have an increasing focus on both data and automation. We have seen this trend increasing rapidly across all industries and across all organisational enabling functions. Understanding both the potential and limitations of technology is critical to organisations. It is also not static (Berente *et al.*, 2021). We have shown how connected devices and increasingly digital operations are creating ever more data and forcing organisations to look to machines to cope. Consumers, regulators, and professional bodies are both accommodating and resisting such technology – resulting in a fluid and emerging landscape. Organisations need a well-defined strategy to respond to both the opportunities and threats presented by automation.

That said, a focus on decisioning technology is unlikely to be sufficient for most organisations. Human judgement will continue to be valued in the absence of perfect data and in the pursuit of exponential business outcomes. Given machines inability to creatively project the future and to address human to human interactions – machines will face engineering bottlenecks. In such instances human judgement will potentially create opportunities for competitive advantage. That said, organisations must be cautious of the inherent frailties associated with the same, together with the resultant data asymmetry. Augmentation can help to support such decisions – but will not eliminate such issues.

The critical challenge for organisations then is making good decisions about where to automate. Our model provides a tool to support such thinking – but will not provide definitive answers. What is clear is that failing to deploy machines as coping pioneers where conditions are suited will likely result in missed opportunity or inability to compete with more progressive organisations. What is equally clear is that for many organisations the bulk of decisions reside in our Grey-zone – where care must be taken to avoid unintended consequences as a result of employee resistance and a proliferation of pilots yielding limited return. Finally, whilst organisations should continue to recognise and value human judgement and experience, they should also recognise the inherent limitations and guard against the same. We have highlighted that automation of decision making will increasingly serve as a competitive necessity and as such has existential consequences.

Chapter 8: Contribution

8.1 Introduction

Our work is of importance for both scholars and practitioners alike. Automation is transforming the way that we think about decision making on a number of fronts. Whilst much has been written about the impact of the same in relation to medicine, transportation, and the military – far less has been reported in relation to organisational decision making. Consequently, our research addresses an important gap in extant knowledge.

8.2 Theoretical

We acknowledged at the outset that a multi-disciplinary approach would be required to support our research question. The existing literature on human unaided decision making is broad ranging, spanning behavioural psychology, economics, and management science amongst others. In a like manner literature related to the theory of the firm is extensive, dating back to at least the 1930s. Literature concerning machines is burgeoning given technology acceleration and application. Each of these bodies of work provides insight into aspects of our research question – but in and of themselves are insufficient. This point is acknowledged by Berente et al (2021) who state that:

> "much of the available research appears siloed. Technical fields, on the one hand, focus on technology and black-box the human and organizational side. Organizational, economic, and behavioural research, on the other hand often black-box, the technological side of AI" (Berente *et al.*, 2021).

Our research addresses this challenge head on, contributing to existing theory by including a broad narrative literature review that links these potentially disparate bodies of literature together to answer a dynamic and evolving question. Our literature review has significant merit if for no other reason than identifying the need for, and contributing to, a multi-disciplinary approach to open questions in our space.

We have built upon the work of Dreyfus (1972) and reframed his notion of *being in-the-world* in light of recent advances in automation. Despite being written as a defensive epistle against the likely encroachment of machines – framed against recent advances it can be considered as a useful test of where machines may be deployed to greatest effect. We have highlighted that the internet of things and growth in connected devices is increasingly resulting in machines being *in-the-world* in a manner increasingly analogous to organic agents. Proximity to the physical world, coupled with machine learning – is enabling machines to overcome the traditional frame problem (McCarthy & Hayes, 1969) and could see machines encroach further into domains traditionally associated with human decision makers. Further we argue that such devices create digital worlds – worlds comprised predominantly of bits and bytes. In such environments we argue that the tables are turned on human agents and that impartial and tireless machines are perfectly adapted to both cope with the volume of data that comprise such worlds and to pioneer patterns potentially indiscernible to organic agents. Equivalent themes have recently been highlighted by a number of authors including Berente et al (2021), Fugener (2021), Lebovitz et al (2021) and Van den Broek et al (2021) – although lack the depth of our account.

We also build upon the existing literature in relation to engineering bottlenecks (Frey & Osborne, 2017). Whilst soft skills have been highlighted by various authors (Makridakis 2018, Frey & Osborne 2013, Autor 2015, Autor et al 2003, Xu et al 2018, Deming 2017, Lee 2018, Brynjolfsson & McAfee 2014, Samson 2020) – we provide two concrete factors that are beyond the current capability of machines. The ability to project or anticipate the future in a non-linear manner is uniquely human – as is the ability to manage interpersonal interactions and relationships. These bottlenecks are likely to see human judgement and experience continue to be prized in high-stakes decision making. We highlight that whilst human capability may result in exponential business outcomes it must be carefully deployed given the plethora of reported limitations associated with bounded decision making.

Our model highlights that the impact of automation is not static. Whilst other authors have described in absolute terms the potential and limitations of machine decision making (Edwards et al, 1992 and Cyert et al, 1956) our model recognises the dynamic and evolving nature of technology. We acknowledge that grey-zone decision making is currently the dominant aspect of our model. However, machines being increasingly *in-the-world* are likely to accelerate encroachment in the coming years. Our model therefore creates a much more dynamic framework through which to consider both the potential and limitations of machines than traditional narratives. This is an important point to note. Given the pace of change, there is a danger that theory is out of data as soon as it is published, we believe however that our work will both retain relevance and evolve over time. We openly acknowledge the fluidity of the modern world and actively encourage academics to revisit assumptions on a regular basis in light of both accelerants and inhibitors.

In a like manner, we have built upon Pickering's (1993) mangle of practice. Our research highlights that the mangle has moved beyond organisational boundaries and is now impacted by consumers, regulatory/professional bodies, and governments. We have argued that the dialectic of accommodation and resistance that traditionally has taken place within an organisation is now subject to forces external to it. We have shown that whilst legislation may curb automation in certain instances, in others it can serve to accommodate deployment by setting parameters within which organisations can safely execute. From an academic perspective this extension or modification of Pickering's theory is of importance. Further, although we have not explored in detail within this paper, we believe, in keeping with Berente et al (2021), that recent advances in machine learning may have altered the nature of machine agency and that the same is worthy of further exploration.

8.3 Methodological

Bailey and Barley suggest that 'a unified approach would help us better understand any workplace technology, it is especially urgent in the case of intelligent technologies because by the time these technologies have been adopted and implemented we will have lost opportunities to influence their design and intent' (Bailey & Barley, 2020, P.10). They equally acknowledge however that 'one might question whether powerful stakeholders who control what technologies are built and who dictate the purposes of their design would be willing to engage with scholars' (Bailey & Barley, 2020, P.10). Scholars to date have largely relied on quantitative methods:

> "For example, to identify the probable impact of automation on occupations researchers have relied on databases developed from standardized descriptions of jobs based on job incumbents' answers to standard survey questions.' (Bailey & Barley, 2020, P.2)

We have been very fortunate to have access to 25 senior leaders in order to inform our research and begin to redress the call for research by Bailey & Barley (2020) and Berente et al (2021) to better understand the powerful dynamics at play here. Our use of qualitative research and in particular Rubin and Rubin's (2016) responsive interviewing technique have resulted in unique and rich access to the knowledge, attitudes, and practices of influential leaders. The depth of response that we were able to achieve, as evidenced by the circa 170,000 words captured in transcripts has allowed us to capture insights from leaders that will be pivotal to the future evolution of the large organisations in which they serve. This unique insight is of significant value.

We have also used our unique access to senior practitioners to test and refine our model. Few researchers are afforded the opportunity to share their models in intimate forums and gain feedback from leading experts. Being able to share and discuss our work has greatly improved our outcomes. Proximity to senior leaders over the course of our day job has enabled us to informally test the level of interest, engagement and influence resulting from our work. This has allowed us to constantly refine elements of our presentation and approach to ensure relevance at the highest levels of organisations. The combination of academic insight resulting from our study, qualitative research with senior professionals and the ability to workshop the resultant outcomes adds a richness and depth to our work that few studies in this space can match. The combination of practical insight and scholarly research has led to superior outcomes to those that might have been achieved in either silo.

Finally, our transcripts themselves are of academic value and interest. Within the scope of this exercise, we have had to be judicial in our analysis of the nuanced data set collected. We fully intend to make this information available to other scholars – albeit in an anonymised format. We expect such data to be of significant interest and benefit to others.

8.4 Practical

Building upon our three aggregate dimensions and supporting discussion we have proposed a model to support both academics and practitioners alike to assess where automated decision making and support ought to be deployed to best effect. Thus we address the call from Berente et al to 'help managers in their decision making with well-developed, evidence based practice' (Berente *et al.*, 2021, P. 1434). We have equally highlighted the circumstances in which human decision making will likely to continue to be valued. In each identified decision zone we have highlighted the defining characteristics of that zone, the proposed automation strategy and associated considerations. These insights are invaluable for informing both digital and talent strategies. Given the rapidly evolving landscape we believe the accelerators and inhibitors play a powerful role in ensuring that our model is flexible enough to be relevant moving forward.

Whilst the theory underpinning our model is of value to practitioners, we have highlighted how our model can be used as a diagnostic tool – providing a worked example of how the tool can be used by organisations to map decisions – before overlaying an automation strategy. The output from this type of exercise can be used to influence decision makers and drive change. The model can be used across industry and function – giving it broad utility.

We have been pleased with the level of engagement from senior leaders and advisory practices. Our research area is highly topical – but often complex. Our model helps to simplify that complexity. We were reminded of the impact of our work during a recent discussion with a FTSE100 board member regarding sustainability and in particular decarbonisation. The challenge highlighted to us was the complexity of the data, system and third-party landscape associated with reporting and influencing scope 3 emissions – a significant issue in achieving net zero. We were asked for our thoughts in terms of how this could be simplified to make it accessible to the board. Whilst this specific use case has not been part of our research – our model for practice works incredibly well in this context. Reporting emissions is a huge data challenge – with organisations grappling with how to capture and report supply chain emissions across thousands of third-party providers. Our work can readily be applied to this area, and we have been invited to submit a paper outlining the approach to be presented to the board in due course. The area in question is evolving rapidly and organisations are increasingly deploying connected devices to report emissions, whilst regulation is emerging to set standards around carbon budgets. Whilst there is a long way to go – there can be no question that machines will eventually serve as coping pioneers in this space. It will be impractical for organisations to analyse such vast amounts of data themselves and driving actionable insight across such data sets will be impractical. Emissions reporting will likely become closed loop systems in the future. Huge opportunities exist for organisations that can lead the charge in this regard – accelerating investment and creating competitive advantage through sustainability – underpinned by automated decision making.

The point of the foregoing is not to pivot to a lengthy discourse on sustainability – but to highlight the practical utility of our work as an engagement tool, from which it is possible to influence senior decision makers and ultimately drive change. The latter is yet to be evidenced but we are very confident. As a partner from one of the world's leading advisory firms noted, 'you can take this into a board discussion, right? And they'll get it.'[253]

[253] Partner for Emerging Technology at Ernst & Young

Chapter 9: Limitations, Recommendations for Further Research & Concluding Comments

9.1 Limitations

Given the temporal parameters of our work we acknowledge several limitations. Firstly, given the broad scope of our multi-disciplinary literature review it was not practical to adopt a fully systematic method. Furthermore, our research area is highly topical and as such new literature becomes available on a daily basis. Whilst we have set out a fair and balanced representation of the extant literature, we acknowledge that a fully systematic review would provide a more complete perspective.

In a similar manner we have had to compromise the depth with which we have been able to address certain phenomena reported in the literature. We acknowledge that our research area is highly nuanced and that we have provided high-level insight, in some instances, to debates which rage fiercely amongst academics. A clear example of this being how technology ought to be designed, implemented and used in light of the resultant social and political consequences, both intended and otherwise (Marabelli *et al.*, 2021).

We set out to conduct a purposeful survey of senior leaders. Whilst this is sufficient to draw inference from our findings, we acknowledge that further work would be required to move our inferences from being abductive. That said, the depth and uniqueness of our insights is among our most significant contributions. We believe that future researchers should not overlook the importance of the explanatory power of qualitative methods and in particular responsive interviewing.

Finally, our discussion topics with leaders were broad. This breadth resulted as a natural consequence of the techniques deployed. Allowing leaders to talk widely on our research topic, whilst gently steering, allowed us to put leaders at ease and encourage them to speak freely. This resulted in great, nuanced examples and insight. Equally, it resulted in significant data that we were unable to fully report in this paper. We have collected enough material for a number of further papers on related themes and we regret not being able to do full justice to the totality of the phenomena reported by leaders.

9.2 Recommendations for Further Research

Our work has done much to progress the debate concerning the impact of automation on the future of organisational decision making. We have highlighted below suggestions for further research.

- **Material Agency.** The nature of machine agency did not play a significant part in our research. We are however intrigued by the notion of material agency highlighted by Pickering (1993). In particular we find that Rose & Jones (2005) assertion that materials can only behave, whilst, humans act, of interest. This was advanced recently by Berente et al (2021). We support Newman et al in their call for:

  > "deeper exploration on the topic of "agency," which is defined differently across domains and cultures, and relates to many of the topics of discussion in AI ethics, including responsibility and accountability" (Newman *et al.*, 2019, P.1).

  We have argued that machine learning will be increasingly important as the scale and complexity of data sets increase. We have also highlighted that connected devices and the increasingly digital operations of organisations is creating digital worlds – which machines are perfectly adapted to serve. In such environments we question whether machines ought reasonably to be accorded a greater degree of intentionality. Are machines likely to in the near future 'construct goals that refer to presently non-existent future states and then seek to bring them about' (Pickering, 1993, P. 266). We believe this is an area worthy of exploration.

- **Soft Skills.** Within this paper we have focused on one set of so-called soft skills – those related to judgement in decision making. We have highlighted that judgement in every day parlance is difficult to adequately capture through definition and is somewhat elusive. We have also highlighted the role that creativity plays in decision making – in terms of enabling leaders to predict or anticipate the future. Whilst much work has been performed in relation to disruption of certain industries and tasks – we believe that the impact of automation on soft skills is somewhat neglected. Where soft skills are mentioned in the literature it is often against a tacit assumption that machines will be unable to match organic agents. We believe that further research is required to unpack this further. If soft skills do indeed create natural engineering bottlenecks for machines, then surely this is an area worthy of further exploration. Tacit assumptions will not suffice.

- **Abductive To Inductive Inference.** We remarked at the outset of our work that deductive inferences are certain, inductive probable and abductive inference merely plausible. We also observed that the importance of generating new management theories in rapidly changing organisational contexts (Saetre & Van de Ven, 2021). We have outlined the contribution of our work and consider it to be of importance to both academics and practitioners alike. That said, we have used abductive inference throughout and acknowledge the limited nature of our data set. Whilst our data set is unique and provides deep insight – we believe that further scholarship is required to move our inferences from being abductive to inductive. This can be advanced by building on our contribution across wider populations, exploring within analogous industries and firms and conducting a systematic literature review.

- **Linear vs Exponential Outcomes.** We have highlighted that the ability to project the future and creatively imagine new ways of delivering products and service is uniquely organic. Such creativity is equally applied to the highest stakes decision made by organisations – those related to capital allocation. We have suggested that data can inform decisions but is considered insufficient – largely because data will project forward on a linear basis predicated on extrapolation of historic trends. We casually suggested that Clayton's (1997) innovator's dilemma would not be solved for by reliance on data alone. We believe developing this idea further would be of academic and practical merit - given that exponential outcomes seemingly result from human judgement, but so to, does bias and systematic error.

9.3 Concluding Comments

Automation looks set to transform the future of organisational decision making as recently highlighted by Berente et al who note that 'the interaction between humans and autonomous AI is perhaps the key managerial decision of our time' (Berente *et al.*, 2021, P.1440). Despite the fact that the 'task of 'deciding' pervades' (Simon, 1945) organisations which have long been plagued by agency conflict – the impact of automation within such entities is strangely underserved. Despite assertions that rational decision making is a unique achievement of mankind (Evans, 2010) we have highlighted that the extant literature suggests that the average human decision maker employs heuristics and intuition without conscious delineation (Evans, 2010). The consequence is that such decision makers are subject to bias and systematic error (Agrawal *et al.*, 2019; Kahneman, 2003). The consequence is that such decision makers are subject to bias and systematic error Human agents satisfice in response to their bounded conditions – resulting in traditional organisations that are 'heterogeneous, boundedly rational entities' (Dew *et al.*, 2008 P.40). Machines by contrast are capable of processing data with tireless impartiality deploying rational, repeatable decision logic at scale. These issues are not new. However, recent advances in technology have seen the associated debate become less abstract and more practical in the light of viable inorganic alternatives. Consequently, we believe that an important question needs to be addressed, simply, given recent advances in automation where and to what extent should leaders consider deploying machines to support decision making in large organisations?

We answer the call from Bailey & Barley (2020) and Berente et al (2021) that scholars research the interests and agendas of those responsible for helping to shape technology and its deployment. We highlight through discussion with 25 leaders that data fuels automated decision making, that human judgement and experience continue to be valued in relation to high-stakes decision making and that accommodation and resistance in the face of technology is increasingly moving outside of organisational boundaries. We find that the most challenging decisions made by organisations relate to capital allocation. Such decisions require that leaders make creative predictions or projections about the future. This soft trait, together with decisions related to, or requiring, human to human result in engineering bottlenecks.

Building upon our results we have proposed a model establishing three organisational decision zones. We have shown that data is growing in complexity and volume – the former driven by large amounts of structured, semi-structured and unstructured data collected through increasingly digital operations and connected devices. Where such data is sufficient to drive decisions, machines serve as coping pioneers. In such instances progressive organisations deploy automation to displace human agents and establish increasingly closed loop systems increasing data democratisation. Within such domains machines are able to potentially pioneer new forms of value from data by identifying trends that are both impractical and potentially cognitively indiscernible to human agents. In such scenarios organisations deployment of such technology is potentially existential.

At the other extreme of our model, we have highlighted that human judgement and experience continues to be valued. High-stakes organisational decisions are characterised by low volumes of data as typified by mergers and acquisitions. Human agents have the potential to create exponential business value by making non-linear decisions, creatively projecting the future. That said, information asymmetry is likely to exist creating agency challenges and both bias and systematic error must be guarded against. Information is likely to augment such decisions but will not in and of itself be considered as sufficient to drive effective decisioning.

We have highlighted that between these two extremes – grey-zone decision making exists. Automation in this space is possible – but will typically result in a large number of individual use cases. In this domain we can expect to see human accommodation and resistance and unintended consequences. Unless and until generic artificial intelligence becomes available – organisations will need to consider their approach to this space carefully. A proliferation of pilots can lead to dilution of investment and poor returns.

Our model reflects the fact that the world is not static and helps to reflect a rapidly evolving environment. Firstly, the increasing number of sensors and connected devices is resulting in the physical world being increasingly and progressively reduced to bits and bytes. As data increases in complexity and volume, decisions are increasingly suited to machines – encroaching into the Grey-zone. Secondly, we have highlighted that accommodation and resistance will increasingly come from sources external to the organisation. Legislation in particular looks set to play a significant role. Whilst legislation is likely to curb certain deployments – it will equally legitimise others. The surety about where such parameters are set will embolden progressive organisations.

Our research makes three material contributions. Firstly, we make a methodological contribution by answering the call to explore the motivations of organisational leaders. Our qualitative research provides depth that has not been possible to extract by traditional quantitative methods. From a theoretical perspective, we contribute to the debate by adopting a multi-disciplinary approach to the literature. In other words, the discussion is not new. Reframing traditional literature in light of recent advances we are able to make material contributions to the work of Dreyfus (1972) and Pickering (1993) amongst others. Finally, we have created a dynamic model for practice that can be applied by practitioners to help inform their automation strategy based on our three decision zones and associated characteristics.

We believe the days of human agents having complete mastery over organisational decision-making are coming to an end and leaders should prepare themselves to share the space with our impartial, tireless, inorganic creation. As noted by Simon & Newell now more than ever we may ask 'less and less 'Are they here to stay?' and more and more 'how and where can we use them effectively' (Simon & Newell, 1958 P. 4). As Berente et al warn, 'managers cannot wait until the future unfolds to understand this emerging and powerful phenomenon' (Berente *et al.*, 2021, P.1445). Our research and associated model go some way towards helping leaders address this potentially existential challenge.

Appendix I – Literature Review Search Words

All searches performed within Scopus database using 'article title, abstract and keywords' in 2019. Formal search augmented by recommendations for supervisor and other scholars and references of interest within key texts.

Search Words	Results	Literature Review
"Heuristics" and "Decision Making"	9,233 Results	Reviewed abstracts from Top 30 listed by no. of citations. Lowest reviewed item 557 citations
"Human Decision Making"	2,728 Results	Reviewed abstracts from Top 30 listed by no. of citations. Lowest reviewed item 290 citations
"Regret" and "Decision Making"	3,683 Results	Reviewed abstracts from Top 20 listed by no. of citations. Lowest reviewed item 339 citations
"Rational Decision Making"	2,161 Results	Reviewed abstracts from Top 20 listed by no. of citations. Lowest reviewed item 352 citations
"Intuition" and "Decision Making"	2,951 Results	Reviewed abstracts from Top 20 listed by no. of citations. Lowest reviewed item 532 citations
"Machine Decision Making"	51 Results	Reviewed abstracts from Top 10 by no. of citations. Note – very low citation rate – at no. 10 on the list
"Artificial Intelligence" and "Decision Making"	21,260 Results	Reviewed abstracts from Top 20 by no of citations. Lowest reviewed item 700 citations

“Expert Systems”	66,279 Results	Reviewed abstracts from Top 20 by no. of citations. Lowest reviewed item 1435
“Decision Support Systems”	105,587 Results	Reviewed abstracts from Top 30 by no. of citations. Lowest reviewed item 1375
“Organisational Decision Making”	1,187 Results	Reviewed abstracts from Top 30 by no. of citations. Lowest reviewed item 119
“Agency Theory”	4,293 Results	Reviewed abstracts from Top 30 by no. of citations. Lowest reviewed item 535
“Mangle of Practice”	45 Results	Reviewed abstracts from Top 12 by no. of citations. Citations below 10 beyond this point
“Dreyfus” and ‘Being in the world”	8 Results	Reviewed all 8 abstracts – all but top 2 below 10 citations

Appendix II – Sample Introductory Email

Dear [ ],

In addition to my current role as Chief Procurement Officer at Pearson I am in the third year of a DBA (Doctor Business Administration) with the University of Warwick. My research area explores the impact of automation on the future of decision making within large organisations.

In order to inform my work, I am interviewing a number of senior business leaders and was very much hoping you would be willing to participate. The interview would last around 60 minutes and explore, in a conversational manner, issues related to human and machine decision making. The interview would be recorded for ease of reference and would be used to inform my thesis and/or a series of thought pieces for publication. Unless otherwise agreed, I would ensure that any references to our discussion are anonymised. All information shared would be held in strict confidence and no preparation is necessary.

I would be very happy to share a copy of my work post any discussion.

Whilst I would very much appreciate your insight – please do not feel obliged. I am in this instance reaching out as an independent researcher and not in my capacity as an officer of Pearson.

Please let me know if you are willing to participate or if you have any questions.

With my thanks in advance

David

Appendix III – Sample Transcript

Interviewee: [redacted]

Role: SVP & General Counsel

Company: [redacted]

Interviewer: David Feavearyear

Date of Interview: 14th October 2021 – 16:30 - 17:30

Method: Microsoft Teams meetings - recorded using Teams

[Small talk to open]

Interviewee: Back in school, is that right?

David: I started my doctorate nearly three years ago now. So obviously it's part-time around my day job. It's a doctorate in Business Administration. So, it's a terminal business degree on the back of my existing MBA if you like. It's with Warwick Business School and like most doctorates, it's research-based. So, I started with grandiose notions of looking at the impact of AI on the future of work and things like that, which I think would have been interesting. But it's so broad that I'd still be doing it in 20 years' time.

So, I narrowed it down to looking at the impact of automation on the future of decision-making within large organisations. Partly because there's lots of stuff in areas like autonomous vehicles and medicine - using machines to help with diagnosis, in the military, they use AI to guide weaponry and things like that. But when you look at the organisations that the likes of you and I work in, we are somewhat more embryonic in many instances around the way that we think about machines and the way we think about decision making.

So, I thought it would be interesting to look at, you know, what large organizations were likely to do with this technology going forward. And to sort of navel gaze a little bit around, what decisions in the future will continue to be made by humans. Where will we be augmented by machines? And where might we just replace humans altogether with automated ways of doing things? So, my research has been largely qualitative. So, speaking to organizational leaders and board members to really try and tease out what they know about this area, what they think about this area and what practices they are applying today. So, I think by the time I'm finished, it will probably be one of the biggest studies of services-based organizations in this area, which,

which I think will be quite cool, because, you know, one of the advantages of my job is I get quite good access to interesting people. [laughs]

Interviewee: Yeah, fascinating, that's great. Yeah, now do you plan to go back into the business side of things? Or do you plan to go more into academia? Or what's your, what's your ultimate goal? Or have you not thought about that yet?

David: To be honest, I wanted to give myself choices in the future. I quite like the idea. I mean, not in the very near future. But in the mid-term, I like the idea of doing some writing. I like the idea of doing some lecturing. I like the idea of traveling, lecturing coupled with advisory, or maybe even doing it alongside a corporate role as it were. But I just like the idea as I move towards the latter part of my career, just having some different options around how I spend my time.

Interviewee: Yeah, the reason I ask is I know we spoke about this years ago. But I've been thinking very much along the same lines. I've been writing a fair amount in the space, more around digital transformation and the law and how that space is developing, but I’ve also been an academic visitor at Oxford for two years. And I just got a real taste for that part of me. And it's something that I can definitely imagine deepening as well. I'd love to do a PhD. There's just no way at this stage. I couldn't fit it in. But at some point, I may follow in your footsteps. I think it'd be a great challenge. And it's hard to, as you say, narrow it down sufficiently. It's probably more fun to write on a broad topic. But the rigor that comes with trying to really narrowly define it and write something very deep, I think, is an interesting challenge. So, yeah, I'm sure it's an exciting project. But anyway, yeah, happy to help.

David: The only thing I’d say if you are tempted to do it at some point, is that keeping notes of all the stuff you're doing is really quite useful, because, you know, a lot of people end up spending their time collating the evidence of what's going on. And the thing that's interesting is, you know, in our day jobs, we're sort of living in it every day. And so, I think if you are half tempted, its worth starting to record some of your sessions. So, you've got transcripts available to you should you decide to do that in future. It’s quite useful.

Interviewee: No, that's a great tip. You're absolutely right about that, I think. I mean, the other thing I've been trying to do is sort of build a network of people, potential case studies, you know, that could be leveraged in the future if I were going to go back and, and really look at it. But yeah, you know, it's a fascinating space, for sure. And your topic is interesting.

David: Thanks. So was really keen speak to you. I know you've looked at the transformation of legal functions. So, I was keen to speak to you about, you know, what your thoughts are, in terms of how far automation is going to infringe on or displace what lawyers are doing today. What's going to be left? I'm really keen to get your perspective in terms of judgement and how you think about that. People talk about judgement, I think quite glibly; a lot of the time, so I'd love to get your perspective on what judgment is. But maybe, if we could just start with your overall perspective, in terms of what you've been looking at what you are thinking about, we can dive in.

Interviewee, Yeah, it's a great question. So, I'd say, you know, maybe how to tackle this? Well, first of all, I think, I think that one thing that's really, really clear - probably not just in the legal space, but in business, in general, is a great misconception - that a lot of my colleagues have - around how technology, whether it's AI, or other technologies should be used in the legal space. is, they think of the technology alone. It's a bit like an analogy I use. It's a bit like me going into a kitchen warehouse, right? And I get seduced by the bread maker. And I start to imagine what the output would be, you know, I'll get fresh bread every day. And so, I buy this big thing, and then it takes up a huge amount of real estate on my kitchen counter. And it never actually integrates with my life. I don't realize until later that I actually don't make bread, or I don't even eat bread very often. You know, actually, I'm probably going to use a rice cooker instead. Then you step back.

So, if you think about that from the legal side, it's sort of buying a contract management tool or some piece of equipment without really thinking about what problems you're trying to solve, what bottlenecks are preventing you from solving those problems, and what are the solutions? Which often involve process and redesign and culture and a whole set of other capabilities and skills, with technology coming in as an overlay at the very end of that.

And so, when you hear about digital transformation, it's that whole process, really, including the change management and all of the aspects that need to come before you can really even begin talking about the technology. So, the bread maker comes at the very end when you redesign your kitchen, and you've got your workflow down. And you understand what the consumers of that kitchen actually need and want, you know? That's where I think the technology comes in is at the very end.

So that would just be one observation - that I think there's very often a misnomer that technology comes in and just replaces this stuff rather than actually - it's proper functioning, at least at this stage in our evolution is augmentation and enablement. And it has its place within a much broader framework of the organizational redesign. And it's only at that end stage, we really can add value.

With that caveat, I'd say there's enormous potential, particularly in law, for technology to automate and augment, a number of things. And, you know, I would say that there's probably a hierarchical evolution, as it were, it's probably the same that you see in other spaces, you know, at the ground level. What's already there today is a range of AI-enabled tools that help filter, categorize, migrate information, documents, and decision making at an elementary level. And it's beginning to move up the scale in terms of its capability to take on greater and greater tasks and compile even more sophisticated components of the legal product. So that's one element that we could talk about.

The other is data and data capture. I think that's a little further out. But it's beginning to come to the fore in legal. So, some legal departments and some law firms are beginning to recognize the power that sits under the hood - the data that they have available to them. It's not yet organized in systematic ways, the data lakes don't really exist in a way you can find in other places. But that is the promise of the future - something that we're really thinking of now is, as we build the legal department of the future for this company, can we design it with a data lake at the bottom that includes legal compliance, perhaps internal audit, maybe some HR data, maybe some Salesforce data, and organize it from the beginning in a way that would allow us to extract insights from it, that would then add value, new forms of value, to the business in terms of faster decision making better predictive analytics, etc.

So, those are some general top-line observations, I guess. You know, and some examples may be interesting, perhaps around that data - the combination of data and AI - in the law firm context that I've seen that are very interesting. By the way, both of them are free.

David: Yeah.

Interviewee: One is a contract X-ray tool. There's a law firm that realized, you know, they have X million contracts in their repository. And while they can't share the personal, you know, the specifics around those contracts, they certainly can compare and contrast and rank certain clauses of those contracts from, you know, least favourable to most favourable in a particular configuration. So, what this tool allows you to do is, you can do two things, one is you can create a new contract, where you put on a scale of one to 10. You say, "I want a governing law clause at seven, I want an indemnity as a five - and it will create a first draft that is numerically based at seven out of ten in terms of being favourable to you - based on a repository of 5 million documents, right?"

And then the other thing you can do is X-ray an existing contract, so send it through the system, and it will come back and rank all the clauses and say, "This one is a very good clause for you; it's an eight out of ten. This one's a very poor clause for you; it's a two out of ten, right?"

Now, further down the line - there are some banks, for example, that are using that technology against counterparties. Where they have been able to scrape out of the public databases and their existing databases, sufficient data from a counterparty, that when that counterparty issues the first draft, they can analyze it against what the counterparty has agreed previously, or in other contexts, and use that against them and say, well, you shouldn't really have an issue agreeing with this change, because you, you've agreed to it 68% of the time that you've negotiated these types of agreements with us or with a range of peer companies.

So that's interesting, I think, an interesting way that AI is kind of beginning to provide qualitative assessments - but nobody's ever going to rely on that machine alone. Nobody's ever going to say, "Oh, well, you know, it's seven out of 10." So, it's really just a way of having a shorthand that allows the human to augment that judgment. And it's a great way for someone like John Fallon, and you know, you can go to him instead of trying to explain to him – "well, you know, qualitatively it's pretty favourable to us, for these reasons" whilst he falls asleep, and remember how John - his eyes would kind of roll up into his head after about 30 seconds, you know. If you could just say, "Look, its seven out of 10 based on 6 million contracts, and if you want more info I'm happy to help you." But you know, I think that's nice, it's a nice tool to have.

So that's, that's kind of one example, I think, of how it's working. The other is in law firms that will allow you to create basic memos of legal advice in comparative law situations. So, for example, there's a labor law firm that gives you as a tool. You have the ability to, for example, if you need to do a compare and contrast of an employment law provision, you know, what does German versus UK versus French employment law say on redundancies and payouts or whatever - you can click on the fields. It will compile a memo for you that basically gives you that information. It's a pretty simple tool, but it clears away a lot of this sort of wastage of time that previously was done and that they would charge you for. It's now become a kind of a, almost a commodity.

And then on the more sort of sophisticated stuff that you pay for. You know, I guess clearly the most advanced places are e-discovery. And, you know, some of the contract management tools, but e-discovery in particular, where you're sifting through many cases, hundreds of millions, maybe even billions of records, to find needles in haystacks to sift documents that would be responsive to a discovery request. You know, there are a number of cases there where you really need to take a massive volume of stuff, and you need to filter it down to something that's meaningful, that can then be searched by human beings and evaluated and assessed.

And maybe the last thing I'll say – and then I want to just hear what you want me to say - is really, you know, I really don't believe that there are a lot of people in the profession, Richard Susskind is the name, you should probably pull up in case you haven't come across him. He's written a ton of books in the space, "Tomorrow's Lawyers or "The end of the professions."

David: Yeah, two of them are behind me actually, the books.

Interviewee: Yes, I know him personally, and actually, I'm working with him right now on a task force; if you ever want to talk to him, I'm happy to try and set something up. But you know, his view is very sort of bullish on technology and bearish on human beings. Right?

David: Yeah.

Interviewee: And I take issue with that, I actually think, the better, judgment is Eric Mendell; if you've ever come across him, he's an IT professor. He's written a lot about robotics and automation. And one of the things that he says is, "If you look at most successful capabilities today, they're not systems that operate entirely autonomously. They're systems that augment human capacity; whether you're talking about cockpit controls, whether you're talking about underwater, deep underwater exploratory technology, you're really talking about systems that operate at their best when they combine human judgement with the ability to crunch data quickly." And usually, where things go wrong is actually where the interface between humans and automation has failed; the design process doesn't work like it should. So that Air France crash over the Atlantic a few years back from Brazil to France, where the plane had some malfunction in terms of its, I think, the external airspeed instruments and you know, basically it was turbulence. And they ended up in a stall. It was a really basic mistake that the pilots kept trying to lift the nose of the plane until they actually ended up stalling and then just kind of dropping like a stone into the Atlantic. And the machines were – the Black-box later showed - were shouting at them to turn down - like, " don't keep lifting, you're going to stop, you're going to stop." And they weren't listening to it; there were too many instruments going off, there was too much information happening at once. And they had two or three minutes to process it, and they just froze. And they got it clearly wrong, and everyone died. Right? And so, he uses that as an example to show that actually, if they had designed that thing to really clarify the key thing to the human being or maybe override the human being in certain instances, you might be in a better, a better state.

And I think that the augmentation point applies to law, too. I think, for the foreseeable future. what's going to happen is a gradual replacement – in fact it's happening wholesale now at the execution level. The sort of baseline stuff that Junior lawyers and paralegals did for centuries, that's going away, that's a commodity, and increasingly, at the higher ends of the profession, it's augmenting what highly paid professionals do. It's never going to – or at least I can't see anytime soon that fully replacing that human skill - but it will increasingly, I think it will increasingly, push that up into the pyramid - where you have a smaller group of highly skilled professionals and a much larger space that's either automated or serviced by human plus machines. But with less highly specialized training. So, you're seeing the emergence of more disciplined, multidisciplinary teams that are servicing that technology.

So, the profession is changing radically, but it's not changing, like - the end of lawyers and, you know, machines will take over everything. It's changing how the law is practiced, who practices it, whether you need a law degree. I think, mostly it's for the better. I think it's giving access to consumers and, you know, businesses in different ways.

David: So, my observation is aligned with yours, which is a lot of that sort of junior paralegal type work has been automated, it's going away. What's interesting is, how do you develop higher-end judgment skills, if you never work through the basics? Because I mean, my brother-in-law is a lawyer who works for an American legal firm. So, billion hours a week, high pressure, no life. But when he started, the work he was doing. It was incredibly basic stuff, you know, stuff that I'd expect a graduate in any discipline to be able to do. And then obviously, you know, he was supervised by a partner over time. He worked through the ranks, you know, he's now a senior associate doing much more meaningful work. But how do you develop the judgment skills on the harder, more gnarly issues, if you've never worked with the basics?

Interviewee: Yeah. It's a really good question. You know, I think at some level - I wonder how much that sort of basic training actually was useful. I went through it too. I was in a law firm, and I spent crazy hours doing mundane work for years. And you get kind of gradually assumed knowledge by osmosis. But I'm not sure that all those hours spent proofreading documents or filling in the blanks on basic forms were really actually utilizing my law degree or gave me a meaningful leg up in terms of the work that came later.

So, I actually think you would have to reengineer. First of all, you have to select a smaller group of people who are going to be focused on the provision of substantive legal advice, and you have to involve them at an earlier age at a more senior level. And give them more insightful, deeper, analytics-driven work. I would almost say it's a bit like, consultants, you know, when you join McKinsey, I don't think they put you to work proofreading for years, I think they put you on a team, often a multidisciplinary team that's tasked with solving problems. And there's probably a senior partner that reviews the output before it goes out the door, and all that but, and they sit in on negotiations, and they get context. And so, I think it's really about redesigning the training of those lawyers to help them upskill more quickly.

And then, at the same time, I think there's a whole new set of skills that needs to be integrated into the education of lawyers. So, technology, project management, ethics. I mean, their whole business skills - leadership, communication - you know, data analytics, the ethics of AI, you know, there are a whole range of skills that you're going to need. You're going to need to rethink how the service gets delivered. And that requires a much more multidisciplinary skillset. It also means that most schools probably need to begin courses for non-lawyers who are going to be working in the profession in some of those areas - multidisciplinary team areas, web designers and software designers and AI experts who understand the law. These are things we don't have. So, design experts, how do you design products for consumer use that are consumer-friendly? You know, and law will probably be practiced in different places, not just in law firms. And not just in legal departments, but maybe in - supermarkets. And yeah, I mean, who knows?

You could, and you're seeing that right now, for example, LegalZoom in the states that is a contract compilation software. Any consumer can just go out there and use – it'll help you analyze your parking ticket and give you advice about how to appear in traffic court. I hear a lot of different niches. You can kind of laugh a little, you know - the city people sort of laugh at the parking ticket guy, those guys are often - the guy who founded LegalZoom, he graduated from Harvard Law School, he's worth hundreds of millions of dollars. You know, so he's laughing last, you know, and that's, I think the promise of the future with technology - you can scale law in ways that are kind of unfathomable to the pinnacle of the profession. You know, I think it's a little bit like Clayton Christensen, innovators dilemma book, you know, dominant firms, in one generation of technology are never dominant in the next because they're just organizationally incapable even if they see it coming. They just can't get out of their high tower and meet the barbarians at the gates because there's too much at stake for them. You know, I'm not sure the changes will come from the law firms.

David: When you think about lawyers, law firms, legal departments, do you think that do you think about them as being decision-making functions? Or do you think of them as being advisory functions to decision-makers?

Interviewee: I think they're both. Of course, at the end of the day, lawyers, advise clients, right? And clients make the ultimate decision.

David: Yeah.

Interviewee: It's a bit of a sort of, like, "Yes, Minister?" Or, it's a bit like the medical profession. I mean, the doctor ultimately, is just advising you on whether you need a stent, you know, but like, you're not usually informed enough to say, "Well, you know, what kind of stent are you using?" "And do I really need that?" And you could get a second or third opinion, but it is one of those things where there's a lot of power that rests in the expert. And so, you know that I think that will remain; I think that's what people pay for is the quality of your advice and your judgments on tricky questions. And for the other stuff, maybe you don't need a human being to guide you.

I think one of the stumbling blocks on the professional is the ethics rules and less so in the UK; I mean, England and Wales have pretty much done away with that. But the US, which is, you know, the largest legal market in the world, and many, many others still have very, very strict prohibitions on the provision of legal services by non-lawyers. And so that puts a natural brake on all of this because you can't have private equity co-owning a business that provides legal services. You can't have non-lawyers running that sort of thing. And so, the evolution here has grown in this weird, deformed way, where basically all the services have to be provided by lawyers, either in legal departments or at law firms. And it's very hard to have direct to consumer access. Without running big risks, and LegalZoom has run huge risks. They've had to take all kinds of steps to sort of argue that they're not really giving legal advice they're just providing forms. And, you know, but it's a fiction, really. And that's been a big break. And it'll be interesting to see, you know, how long does that break exist?

It's tricky because, in the US, the lawyers were very crafty back in the 1920s when these rules were put in place. The early 1900s, when you had sort of the expansion of large corporates that didn't want to pay these pesky lawyers, and they wanted to do it themselves. And lawyers realized they couldn't go to Congress and get a law passed because JP Morgan controlled Congress and Vanderbilt controlled Congress. So, what they did was they went to the courts, and they got the courts to enshrine these rules as part of the legal, ethical obligations that exist, and so they're, they're mandated by courts, which are unelected bodies, that the politicians can touch.

And in a way, it was a great move from their side to protect their industry. But it's frozen things in a way that's really hard to get at. Because you have to convince judges that it makes sense to open this up and judges are lawyers too, right? And so it's kind of this self-regulating frozen in time thing that is protected.

David: Yeah, and I think legal privilege falls into that camp to my mind because all the time that you can only make disclosures to a lawyer - it prevents, to some degree, you from having an open business conversation in the absence of a lawyer. Which, I guess, is quite a smart way of ensuring that legal always have to be at the table.

Interviewee: Right. And in fact, it goes beyond that. In the US, you can't have a conversation about the law with a non-lawyer without that non-lawyer running the risk of going to jail, for you know, operating without a law license. You know, so it's really hard, and you can't even get, you know, good paralegals to give auxiliary advice on things that they probably know, way better than any lawyer, which is ridiculous in every other profession. You know, you have practitioners, nurse practitioners, and you have lots of other really qualified professionals who can dispense medical advice without the doctor being present. Not the case in law. So, it's a really; I think it's a terrible barrier.

On the other hand, you know, there are some people who say, "Well, if it was such a barrier, then why don't you see this blossoming in the UK?" So, it's not just the regulatory thing. I mean, there are deeply embedded structural, organizational barriers of entry. You know, let's face it, I mean, you know, if you're, if you're going through a divorce, or you're disputing your dad's will, or you're about to do the buyout of a lifetime for a company - you are not going to go to Sainsbury's or get it done online. You know, you are going to hire a proper lawyer who's going to tell you what to do. And there is still that reluctance - at least at the higher end, higher stakes stuff. You still want a human being kind of guiding that decision-making process, right.

David: That piece about judgment. What does that mean to you? I mean when you talk about somebody having good judgment or bad judgment. What's your view on what that actually means?

Interviewee: Great question. You know, I think there are a couple of elements that go with that. One is experience. I guess there are a couple of ways to think about this in a legal context. In the legal department context, which is the world that I operate in, so much of it is making judgments about whether something is an acceptable risk. And that's really hard to put a quantification on. If we acquire this patent, start to manufacture the product, there is a risk that another company that holds a similar patent will sue us. And then there's a risk that they'll win. You know, and it's a risk on risk. And that risk manifests itself in monetary ways and perhaps in reputational ways. And I think good legal advice is about applying experience to that judgment call. What’s the least risky path, or the best path - the best way to incorporate that risk into your decision making.

I do think that there is often a lack of awareness among senior lawyers of the role that data can play in helping augment that judgment, you know? And that I think is to the detriment of - so, for example, in evaluating a litigation risk. Should I settle? Or should I fight this? It's super helpful if you have some tools like - some that exist now that involve predictive analytics around a particular judge. What is the statistical ratio of the judge ruling in favor or against you on this type of matter? Looking at that judge's docket going back through their career or that district, right, and it gives you a probability, a statistical probability, of your likelihood of winning or losing. That's not a certainty, but it's certainly a helpful variable. And I think so, I think that judgment call, which is more of a gut feel or based on experience, can be augmented by data.

So that's one thing that you might think about judgment is this kind of murky gut feel augmented by data.

Another one is I think, good lawyers who have judgment are trained - Jim Collins actually said this to me, and I thought it was a very good observation. He said, "In Business School, you're taught to give the right answer. And in law school, you're taught to ask the right question." And I think lawyers are really good at asking good questions. So, not necessarily giving you the answer, but saying, have you considered X, Y and Z? And have you thought about this? And how are you going to tackle that? And helping in a very methodical way to build up the risk profile and scope out what you need to consider. And I think that's an element.

Finally, I think there's a piece around analytics. Lawyers are very good at - piecing things together in a way that helps you think through the process. So, you know, there were three things you really need to consider in your, you know, in your decision making 1-2-3. And, you know, "taking those three things into consideration, my studied judgment would be that there are two possible outcomes A and B, on balance, I'd recommend that for the following reasons." You know, that that sort of structured way of taking a mass of different variables, putting it together in some framework, and helping the decision-maker arrive at a decision is a skill that only comes with time. And it comes with having seen those sorts of things many times before.

So, I think it's a combination of those three, that sort of gut feel, data augmentation and sort of being able to leverage that. And just that ability to frame and analyze and ask the right questions is probably the way to go, you know?

David: That makes sense. One of the things I think is interesting is, in certain contexts, if you talk about your past experiences as a predictor of the future that enables you to make good judgments, that would be considered a valuable asset, as it were. In other instances, if, rather than calling that same thing experience, you call that bias. Bias comes with a whole bunch of negative connotations. And I think the delineation between bias and experience is quite interesting because one's desirable, and one isn't. But arguably to a greater or lesser extent; in certain instances, they're both predicated on past experience and your prediction of what might happen in the future.

Interviewee: It is a great observation. And, you know, I think that's a really nice hook to plant the sort of question of where does data actually help us? Right? It came back to the sort of the cockpit analogy that we talked about. That would have been a perfect moment where the machine could override human bias - the panic, the sense of, "I feel like I have to keep bringing this nose up" - you know, when it's the exact wrong thing to do, right? Or a doctor, a skin doctor, you know, I'm sure you've seen this. What's his name? Sebastian Thrun in Silicon Valley. I think he was a key part of Google X. But he developed this, you know, AI skin cancer app, you know, that is, like, 98%, more accurate and more accurate than 98% of dermatologists in identifying skin cancer from a cellphone picture, right? You want that sort of thing augmented; maybe that's the first line, first cut, right? I can give you the data set. And that will inform your decision. And then you overlay that with some human judgment. You can call it bias. You know, and I think we need to be very, very observant of that. And maybe technology can help remind us of those biases or put some guardrails on it. But there is a sense of - I don't know what it is. But it's, there's something in someone who has done something for 30 years, whatever that thing is, that they might not be able to fully explain themselves, but that is valuable. I was reading the other day about a forgery; it was a great Greek Roman statue that was unearthed and the Metropolitan Museum of Art was trying to decide whether to buy it. And if it was genuine, it was one of the most priceless discoveries in modern history in terms of its intactness and beauty. And all these experts had considered it in a very studied way. A lot of facts and concluded it was accurate - it was genuine. And then one of the most experienced art experts in the world was invited to come and look at it, and he said later, he described it as, just the second, he saw it, there was something about it that was off. He couldn't explain what it was. But something in his gut told him that, "That's fake." "It's just not real." And it was that intuition that sort of led him to do a whole bunch of other things that ultimately proved that it wasn't real – it was fake. And people worked back from that and said, "Well, how - what is that?" Is that mumbo jumbo you know - or is there something there - that we're a complex organism, and we bury all kinds of things - and we put things together in weird ways that AI doesn't do? And maybe that augments and supplements, that maybe the bio is actually an overlay that's helpful, at some level, you add a flavor to something that otherwise would be very regimented, and logical, but then the world isn't always logical.

David: It's funny, there's a, I think, it's called Polanyi's paradox, which is the idea that you know more than you can tell. So, exactly to that point, you know there are certain things that humans are just innately good at intuitively but that we struggle to explain or describe. Which makes it very difficult to replicate via a machine or process as it were. But we're just inherently good at them. So, to exactly your point, I think that's a really interesting piece about judgment because I think if you could make it repeatable, then you could probably automate it somehow.

Interviewee: Yeah, it's that judgment, it's the high-stakes stuff. you know. One that you might want to think about is sort of, if you were facing capital punishment, and you had the choice between a jury and a human judge, or an AI? And you were told that the AI is actually 99% more accurate? Or, you know, is 99% accurate in its outcomes in recommending the death penalty or not? Whether you're guilty or not? Would you? Would you choose AI? Or would you choose that human jury and that human judge? Would you want to grasp at the humanity aspect, that there's something about human to human, there's something about when you look someone in the eye. Sometimes people get spectacularly wrong, like George Bush, looking in Putin's eyes, and, you know, understanding him or whatever, you know, is ridiculous, right? But there is something about that sort of gut instinct of whether someone's telling the truth, whether you feel like this person is reliable - whether it's body language, whether it's small facial variations. You know, heartbeat - there's studies showing that one of the reasons it's so hard to interface on zoom is that when you're actually in person your brain can actually read in some bizarre way - heartbeat, blood pressure, all kinds of nonverbal clues coming from across the table - that you're not picking up on a screen right, and certainly an AI would have trouble deciphering. Not that they'll never do that. But, so, I think you're right - maybe it's that high-stakes, high-end element of any profession where I think the augmentation is going to last for a long time, it's going to be hard to replicate it and hard to generate trust.

David: There's a philosopher, who was writing in the '80s called Dreyfus, who wrote a great book called, "What computers can't do?" And he wrote an epistemological defense against machines on the basis that he argued that "Machines could never be in the world, in the same way as the humans are." So, they can't interact with the world. They're not designed to spontaneously understand it, interpret it, and be able to respond to it. And therefore, machines would always have limitations against human beings.And I think I think in the '80s, that was a very, very strong defense against machines.

I think the thing that's changed potentially between now and then is the amount of sensors, the ability that machines have to take data, to interpret it in three dimensions and to be *in-the-world* in a similar way to a human being. I think almost the last bastions of that - are exactly what you're describing - the ability to read a human being - to be able to react to a human being. You know, we're nowhere near that from a technology perspective. But I think if you think about most of what a lawyer does, I would argue that machines can interpret that data as well as we can, but it's that last bastion. It's that last hurdle. In my job and in your job - we have to read someone because we have to determine not what they could do – but what they are going to do. And that's the thing, that it's very hard to replicate.

Interviewee: Yeah, and from the client perspective, what should I do? You know, and I think, again, I think it's not a, it's less about at the lower and the mid-levels of the profession – where it is a binary replacement – a machine that can do this better than a human being. At the higher levels of the profession it's about augmentation. And I think it will be a long time until people feel comfortable saying, "Well, I don't really need any human expert giving me any guidance on this because the machines are telling me to go ahead and initiate this lawsuit in Saudi Arabia or, you know, fire this employee because the likelihood is that they committed a code of conduct violation," or whatever the issue is. I think it's, I think it's at the higher-end where the augmentation will come into play.

Now, all that said, again, even the lower-level stuff, I think we're far away from the self-service world where you just push a button, and what you want comes out in a perfect form. And so, I think what you're still going to need is a whole new set of disciplines around crunching analytics, configuring the automation, and the algorithms in ways that are useful to people. Thinking about the customer experience, all of these sorts of multidisciplinary capabilities will become a growth area, at least for the next 20 years.

It's a growth area in the law. And you know, a smaller and smaller number of people will be those sort of Silverbacks that work at magic circle firms. And that's not even where the big money will be made in the future. There will always be big money there. But big money, really big money will be made in developing new use cases. That's where the smart money is going to be in the next ten years. I mean, if I were coming out now, I wouldn't go - I went to New York and worked for a big city firm – I'd probably go the other way and go to Silicon Valley, and I'd be working for the LegalZoom guy. That's where the real stuff is going to hit. So, you know, then there's a whole growth industry around just the mechanics of this digital transformation, and how have you wire law firms and legal departments and companies to leverage all of that? It's complicated. And that's, that's going to be the growth areas right?

David: Final question. Then, I'll leave you in peace. When you think about decision making, and maybe this is something that will change over time, do you think about it as being a hard skill or a soft skill?

Interviewee: I think it's a soft skill, ultimately, but it needs to incorporate hard data. You know, that's the trick. And, you know, I think if you think about, oh, what's his name? "Thinking, Fast and Slow." He is an Israeli economist… Daniel Kahneman. He's been so good at revealing the biases in humans, our lack of knowledge. I think we need a healthy dose of respect for that. So, I do think it's that augmentation of soft skill, judgment, ability to frame things in the right way, the ability to ask the right questions, as it were, and then incorporate within that the aid of tools that have a better way of understanding the things that we really don't understand very well. And it's a combination of those two. I sat next to Garry Kasparov at a dinner once - fascinating conversation. He was telling me about, you know, when Big Blue beat him and the feeling he had. Then how, a few years later, a couple of human beings, regular average chess players, not grandmasters. Good chess players, but not amazing - with a couple of laptops beat Big Blue.

And it was a combination of humans and technology that actually was a winning formula. And I think there's so much truth to that. Whatever you're looking at, a couple of other things that I think are important. I don't know if you've ever read the "Knowledge illusion?"

David: No.

Interviewee: It's a very interesting book. I don't remember the name of the author. If you Google it, you'll find it. But the focus of the book, the core premise is, people, operate under this illusion that they know more than they do. About a whole range of things. It turns out we know almost nothing. So, for example, you know, they did a whole bunch of studies where they asked people, "Do you know how a toilet works?" People said, "Of course, I know how a toilet works." "Well, okay. Can you explain to me how a toilet works?" You know, and then they start to realize they don't understand why the pipe is an S. When you flush, why does the water stop? And how the flushing mechanism actually works? Where does the water actually go? Why does it come back up the way it does, and not to mention how you make ceramics and plastics and how you actually manufacture the toilet? And to really understand how a toilet works is a massively complicated thing, right? And the same thing with, you know, bicycles. You ask people to draw a bicycle, well, where does that chain actually go? And how does that connect to the gears? So, it turns out people know nothing. And conceptually, things like, "Do you know, what was the cause of World War I?" "Oh, yeah, I know that you know, I learned that in school." And it turns out, our knowledge is, like, so superficial, and so skin deep on virtually every subject to the exception of maybe one thing that we do really well. And then, you know, they ask the question, well, how is it that if we all walk around with this illusion that we know more than we do? How can we possibly have sent a man to the moon and developed mRNA vaccines? Like, how is that even conceivable? And the answer is, you know, our brains have evolved to rely on other people for collective knowledge and I think it's a really fascinating concept because machines fit right into that. There's no reason why we can augment that collective knowledge with AI and actually be even better at what we do. And so, it's just an interesting angle to think about.

And then on the law side, I guess the other one that we didn't get to. I'm working with Richard Susskind on a panel that's been convened by the Master Of The Rolls to look at the future of courts in the UK and sort of how should technology - how should the courts be thinking about the use of technology and access to justice. You know, the vast majority of people currently have no access to justice they can't afford a lawyer? Most disputes around the world are just either resolved with violence, or they're just not done. So clearly, something has broken. The law is inaccessible. People don't understand the words; the process is ancient. It's all very kind of quasi-religious. And people are sort of terrified of it.

Are there ways that we can create electronic online courts where artificial intelligence provides you with legal counsel and helps you craft your case? And maybe that case is decided by a Judge - and maybe that judge is augmented by technology? Are there ways that we can actually speed things up? So, courts, that have years of backlogs can suddenly just move really, really fast? And you could have accelerated appeals? And you can gamify it in a different way? But what are the risks of that? Right? And where, where's the limit of tolerance? When your life is at stake? Or your money is at stake? Or how willing are people to go, you know? Do you create a two-tiered system where you have a more human-centric court for people who can afford it and mediocre for the rest?

David: Do you think the you'll be able to resolve those questions? In our day jobs, we talk about equality. But when you talk about autonomous vehicles making a life and death decision. About who to save and who to hit - we're no longer equal. You're going to have to be stacked ranked in an algorithm.

Interviewee: Yeah, I think it depends on how ambitious we end up being. I mean, we just kicked this off. I think that if you narrow the scope down there are some practical, operational ways that courts in England and Wales can adopt technology to address some of those issues in the next, let's say, five years or ten years? Start with some really basic stuff like online courts? This clearly should be something we should be looking at. Right, that we can have zoom-based hearings, you know, and then move into, could you have some auxiliary support for small claims?

And so, I think you can start with sort of the low hanging fruit. And you don't necessarily need to address - will we have fully automated courts in 30 years? Who knows? Maybe. But I think it's just too far out. And there's too much exponential change happening that nobody really knows.

David: I was talking to a member of my team today, and they're going through a divorce, and he made a settlement proposal to his wife; his wife's lawyer rejected it and came back with 25%. His next question to his lawyer was, "Okay." "Well, if I go to court and fight this, how close to 50% am I likely to get? Versus the 25%, I've been offered." "Because clearly, if we're arguing about five grand, then, you know, let's get this done." And it struck me as he was talking - things like that ought to be almost formulaic. And if you get to court, the answer is going to be that number. Unless there are really, really good reasons why that's not the case. And it would circumnavigate so much of the anger and everything else associated with the financial assessment associated with divorce. But it just really resonated.

Interviewee: And then, on the other hand - in that example, you know, again, it comes down to the sort of fallibility of human beings. Divorces are messy. They're rooted in deep-seated anger, and betrayal, and all kinds of crap that has nothing to do with the money. And you could have a rational, you know, well split the difference, or offer her 2000 more, and let's be done with it. And people say, "Are you nuts? I'm not offering that bitch a dime." You know, and they'd rather burn the whole house down. And that's where the human, a good human divorce lawyer can take some of the heat out of that, take them for a drink and say, "Listen, I hear you. She's a bitch. But, you know, in the end, think about your kids. I've seen people die of cancer because they got so stressed." And you know, and you can have those conversations and try and relate on a human to a human level where emotions - the law is a place where emotions get really jumbled.

And it’s not just that divorce level. You know, young couples in this world get really emotional about, "Somebody cheated me." Right? "That company cheated us, and we're going to sue them." And you can say, "Look, it's a really bad idea to sue a prince in Saudi Arabia, you know, and well, what's the legal assessment?" "Well, we have a good case on paper." "Well, great. Sue them." "Well, yeah, but, you know, John, you're going to find yourself 15 years from now, still in the Saudi courts," And it's not about the law; it's about the reality on the ground. And so, there are complexities that I just...

David: It's funny, I was on holiday in Indonesia. And every day I’d ride on a boat with this other couple. Turns out that the guy was a mediator. So, we got talking a little bit, and he said, "Yeah, one day when we're out, I'm going to give you a crash course on mediation - it’ll take an hour." Afterwards, when I got back to my room, he’d made me this handwritten certificate. Because there's no Wi-Fi there or anything else - there was no way of looking this guy up, and I had no real idea who he was - aside from getting a sense of his lifestyle. He said to me, he was famous for negotiating mediations in 48 hours. That was basically his thing. But it turns out he was the guy that mediated the settlement between Zuckerberg and the Winklevoss twins over the ownership of Facebook.

But he said that oftentimes in big corporate disputes. First time that the people that actually need to make the decision get an unbiased view of their position is from a good mediator. Because prior to that, it's been filtered up through the organization, they get told what people think they want to hear. He said the first time they often actually get an unbiased view of the strength of their position is when he goes in. I just thought it was a really interesting observation.

Interviewee: Yeah, there's organizational, you know, organizational - what's the right word - pollution effectively, that skews, what is the rational outcome, right. And then there's sort of; there's a really interesting book called "Never split the difference." Which is written by a former hostage negotiator for the FBI, in sort of taking business schools to task about you know, the zone of possible agreement, and you know, what's your Zopa? All the theories that we learned and, you know, in terms of optimal negotiating and decision making. He said, "None of that really works when you're dealing with a hostage situation." Where you've got a bank robber stuck in a bank holding people hostage, and they need a helicopter and a million dollars. You can't just split the difference; "Well, shoot one of the two hostages, and I'll give you 500." You know, it's not going to work. So, it's, and he said, the key in many of those situations is empathy. And it's about human understanding down to the mundanity. He describes kidnappers in Haiti, where they kidnap people on a very regular basis. And how, you know, the negotiation starts on a Monday with really high numbers. And by the time you get to Friday, actually, the kidnappers just really want to have their weekend. And, you know, it goes from 100 grand down to 10. And, you know, he'll be like, look, I'll give you seven and a half in cash in the next two hours, and there'll be like, fine and you can hear them in the background getting ready to have their Friday night beer. And they just want to get this thing done, right. And that's not rational. But there's that human element that good negotiators, good closers, cut through the organizational bias, they cut through the human messiness, the emotions, I just want to go have a beer, even though that makes no sense.

For an AI, that would make absolutely no sense. You know, and so that needs to be factored in. And I, you know - I don't know - I'm a sceptic, I think there are areas that will be easier for AI to move quickly up the ladder. I really do think in the higher ends of the profession where that human stickiness comes in - complexity; it's going to be very hard for an AI to meet the needs in a high stake’s environment quite the same way it will augment it.

David: My view on this is, it can only happen if you have machines interacting with machines. Right? So, if you removed humans entirely from the negotiation process, for example, that might work. Okay. I mean, you could end up in an infinite loop because they might never agree, but you can't have a machine versus a human. You couldn't have one using the analytics, for example - because to your point; there's too much emotion, there's too many other things going on in a human being's mind.

Interviewee: Yeah, because if you think about what the law really is, it's humans organizing things for humans.

David: Yeah, absolutely.

Interviewee: And it interfaces with big things like justice. It's stuff that people care about, and you know, that has a price tag, that's hard to, you know, it's hard to really, can you really replace it entirely? You know, I don't know, over time, you know, 50 years from now? I don't know how many of us will be doing anything. One promising area that we haven't touched on is blockchain. And that, I do think, has some big runway in the legal space in terms of automating a lot of transactions.

David: I agree. And I still can't work out why blockchain hasn't been more successful and isn't more prevalent than it is because it just makes so much sense. I mean, if you look at my space, for example, suppliers due diligence. Every day, you've got hundreds of thousands of man-hours being used to do exactly the same assessment on exactly the same suppliers for exactly the same purpose. Why not do it once – put it in blockchain and just enable other people to access it and pay you a royalty fee?

Interviewee: I agree. I think it's probably just that the complexity of building in the infrastructure to make that happen in a low transaction cost away is not yet there. But it's coming. It's got to come. It's just it's obvious.

David: It's a trust-based system. And I think that's the challenge. The whole climate agenda is another great example of blockchain. You know, it feels like everybody wants to be waving their banner from the hills talking about the amazing work they're doing. Whereas, actually, if you use blockchain so that everybody could benefit from the amazing work they're doing, then you'd have a far bigger social and environmental impact, I think. But there's still s wish to I think want to be the market leader. And I don't think fundamentally; organizations want to work together as collaboratively as blockchain would require.

Interviewee: Yeah.

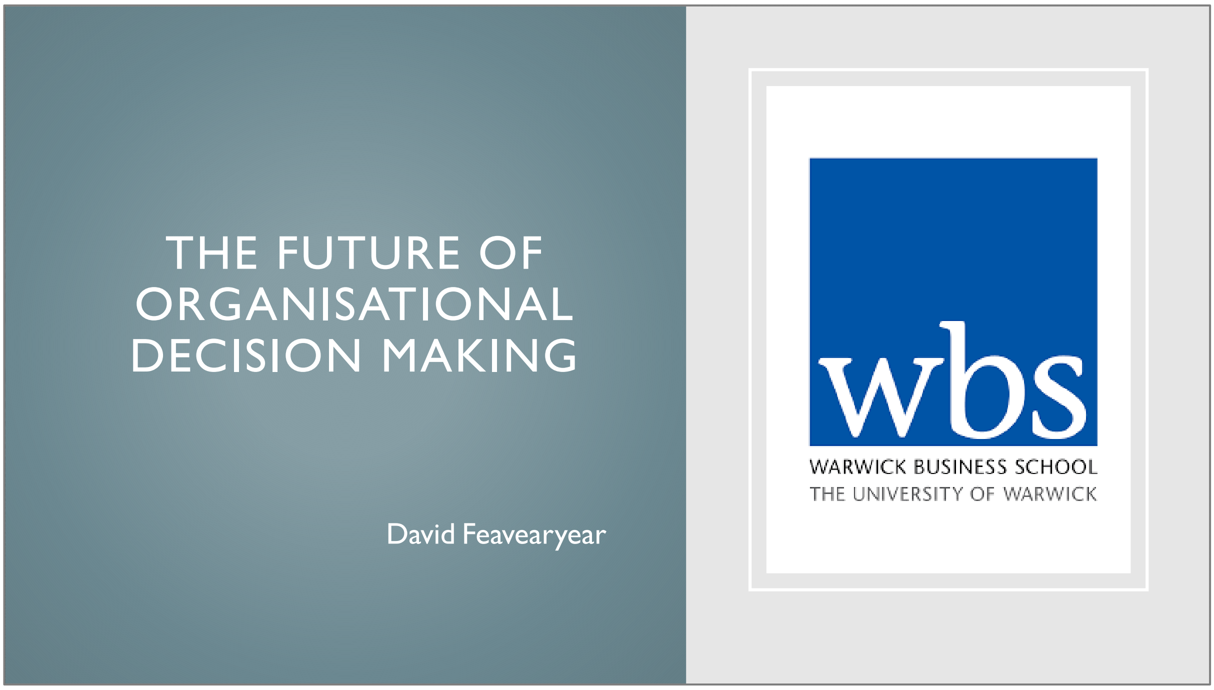
David: I’ve taken far more of your time than I anticipated. So I really, really enjoyed the conversation.
Interviewee: Yeah, likewise, David, and keep me informed. I'd love to hear where you end up with that. And actually, we should just stay in touch. Generally, we have a lot of interests in common. So, it'd be interesting to just stay in touch and catch up a bit.

David: Okay, I agree. Fantastic. Thank you so much. Cheers.

Interviewee: Thanks a lot. Bye.

[End]

Appendix IV – Feedback Workshop Briefing Slide Deck



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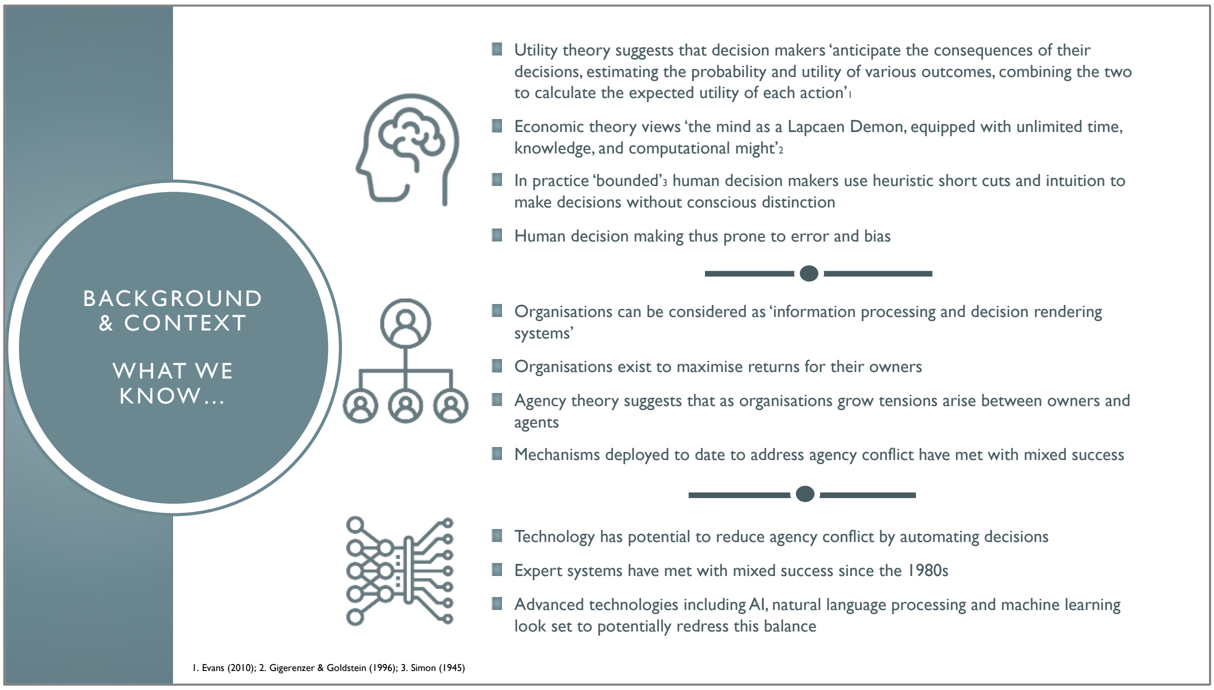

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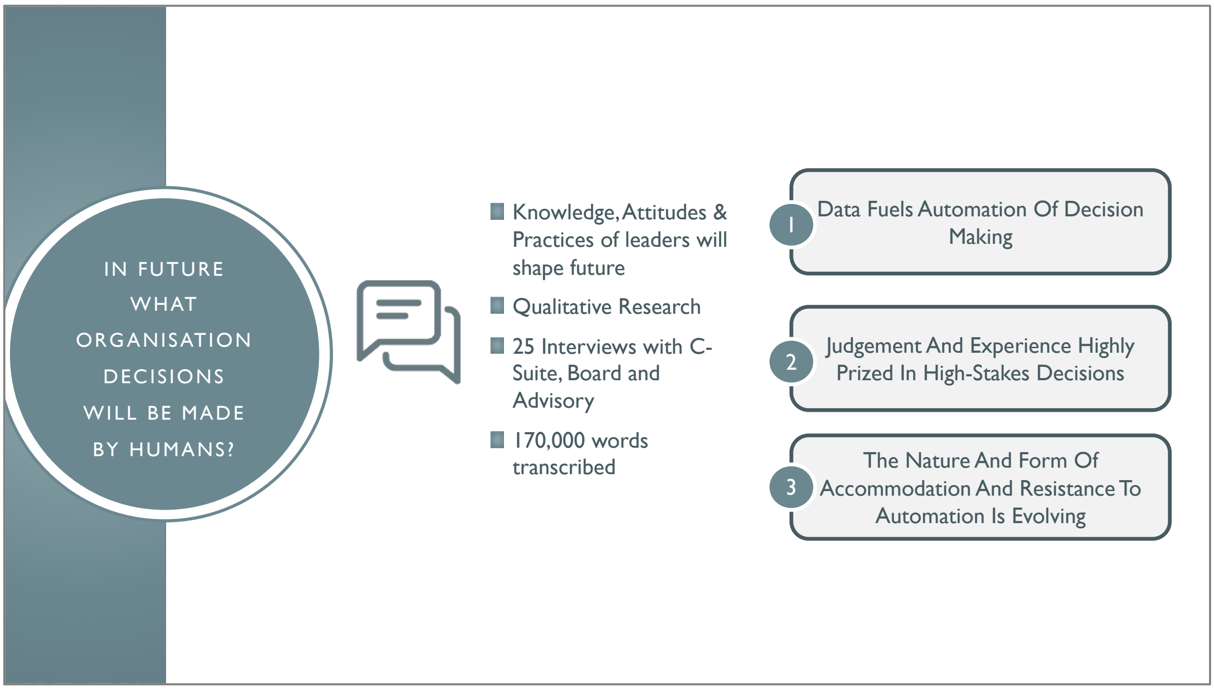

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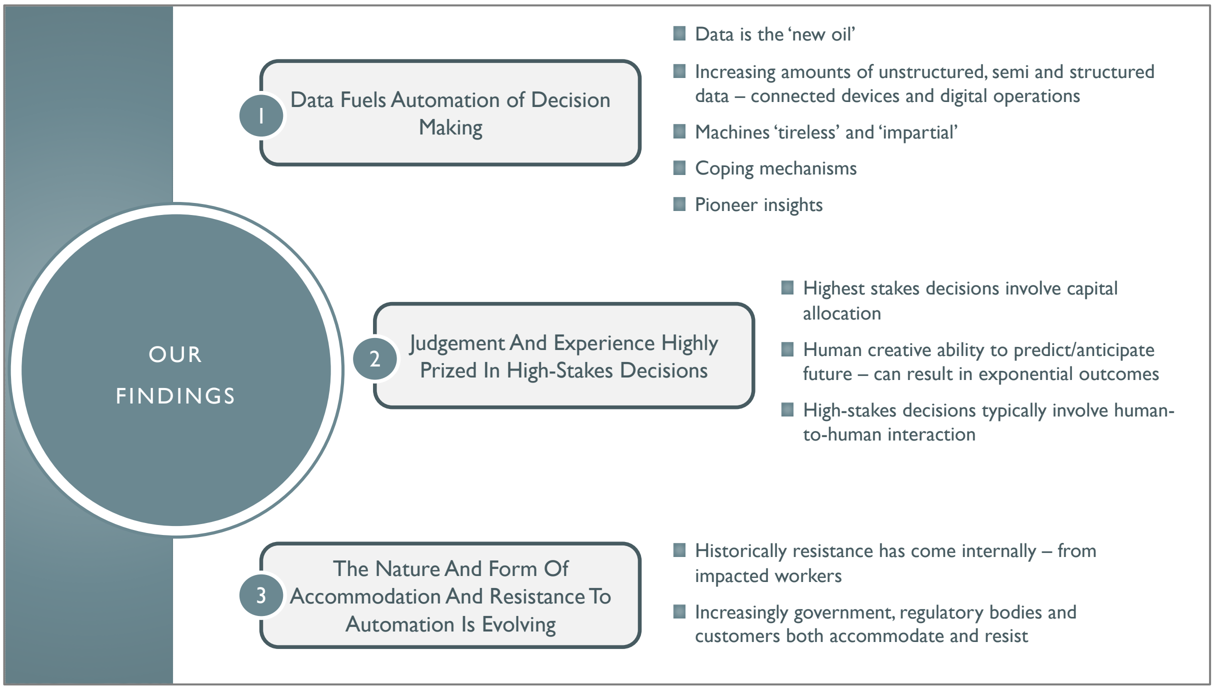

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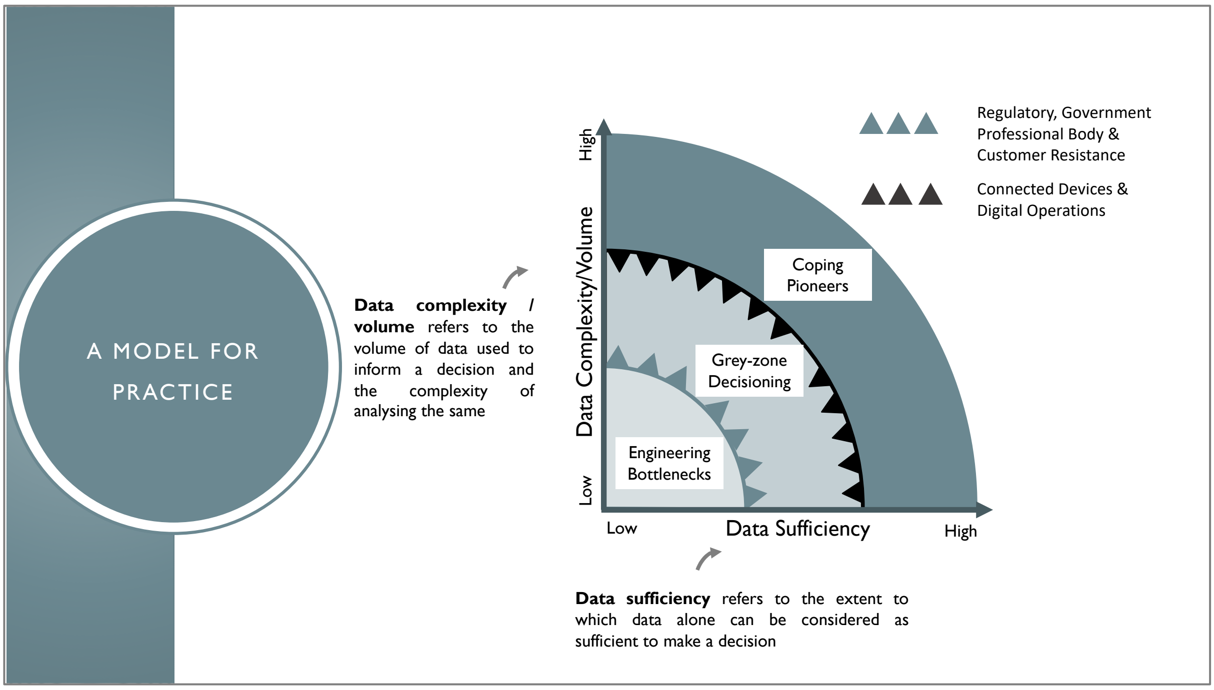

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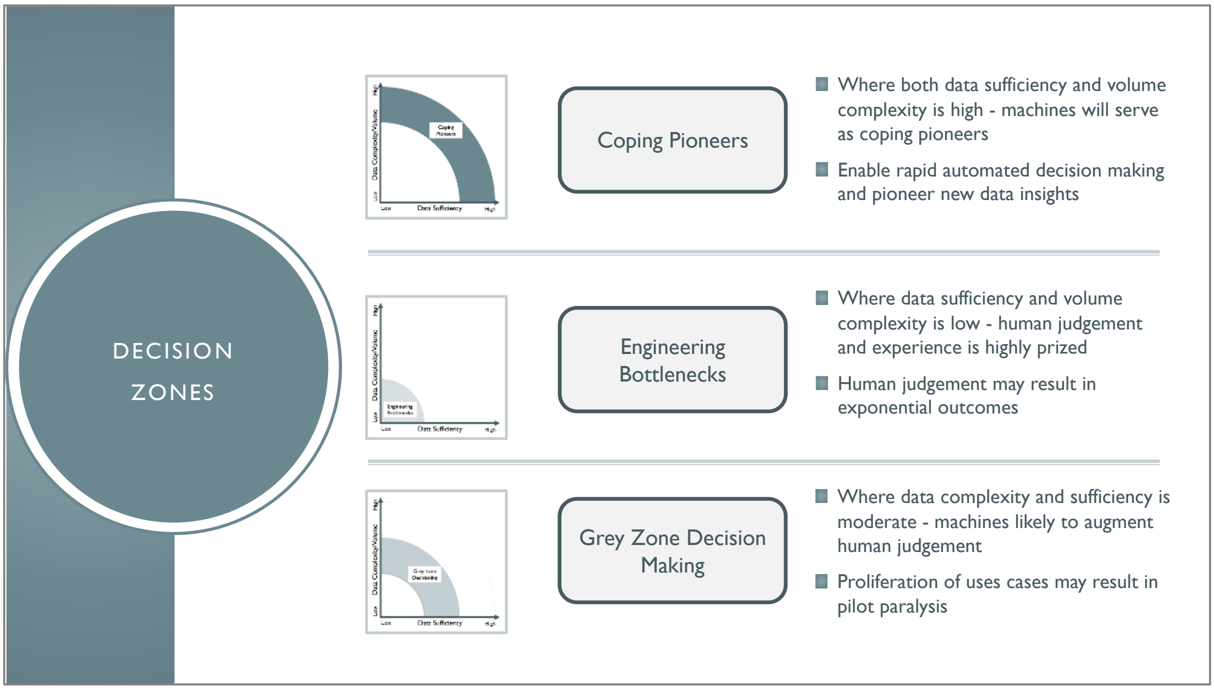

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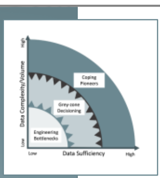
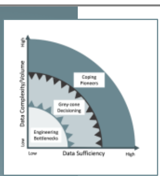


MACHINES AS COPING PIONEERS

Decision Zone Characteristics	Automation Strategy	Considerations
■ Highly repeatable, hard decision processes at scale ■ High volumes of data (structured, semi-structured and unstructured)	■ Machines deployed as coping strategy ■ Machines used to pioneer ways to exploit data ■ Data democracy enabled ■ Limit/eliminate human decision making	■ Machine learning necessary to maximise value ■ Machines will displace human agents ■ Closed loop processes may enable zero touch or lights out processes ■ Competitive advantage if early adopter ■ Competitive necessity if early follower ■ Robust data strategy required to collect and exploit data

Decision Example: Credit decisions in financial services. Decisions are highly repeatable and largely data driven, closed loop processes. Whilst exceptions may apply – vast majority of decisions will be automated enabling organisation to cope with complexity.

Slide 7

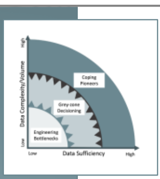


ENGINEERING BOTTLENECKS

Decision Zone Characteristics	Automation Strategy	Considerations
■ Low volumes of data – including semi-structured and unstructured data ■ Low volume, high stakes decisioning ■ Decisions require either projection of future and/or human to human interaction to enable	■ Machines deployed to augment human decisions ■ Human judgment highly prized – characterised by experts	■ Need to be cognisant of bias ■ Decisions will be subjective and prone to error ■ Data asymmetry likely to exist between decision maker and both board and shareholders ■ Exponential business outcomes may be achieved ■ Human judgement may be a competitive differentiator

Decision Example: Acquisition. High-stake capital allocation decision where projection of future state is required to inform decision. Decision is likely to involve significant judgement in the absence of hard data to support decision making.

Slide 8



GREY-ZONE DECISION MAKING

Decision Zone Characteristics

- Moderate levels of data – both structured, semi-structured and unstructured
- Decisions require a mix of hard and soft decisioning processes
- High volume of moderate value decision processes

Automation Strategy

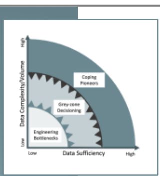
- Use case specific automation – may involve partial automation of process
- Focus on high impact processes

Considerations

- Care should be taken to avoid automating processes without tangible return
- Avoid pilot paralysis
- Automation strategy may result in resistance
- Machines will augment rather than displace – may result in human in the middle
- Human agent resistance may be significant and result in dialectic of accommodation and resistance
- Need to be cognisant of bias
- Decisions will be subjective and prone to error
- Data asymmetry likely to exist between decision maker and owners

Decision Example: Business case for customer acquisition (e.g. sales proposal). Rational decisioning models will be used to calculate margin, cashflow and balance sheet – but will be heavily informed by input from human agents. Judgement required to determine sales price in competitive situations.

Slide 9

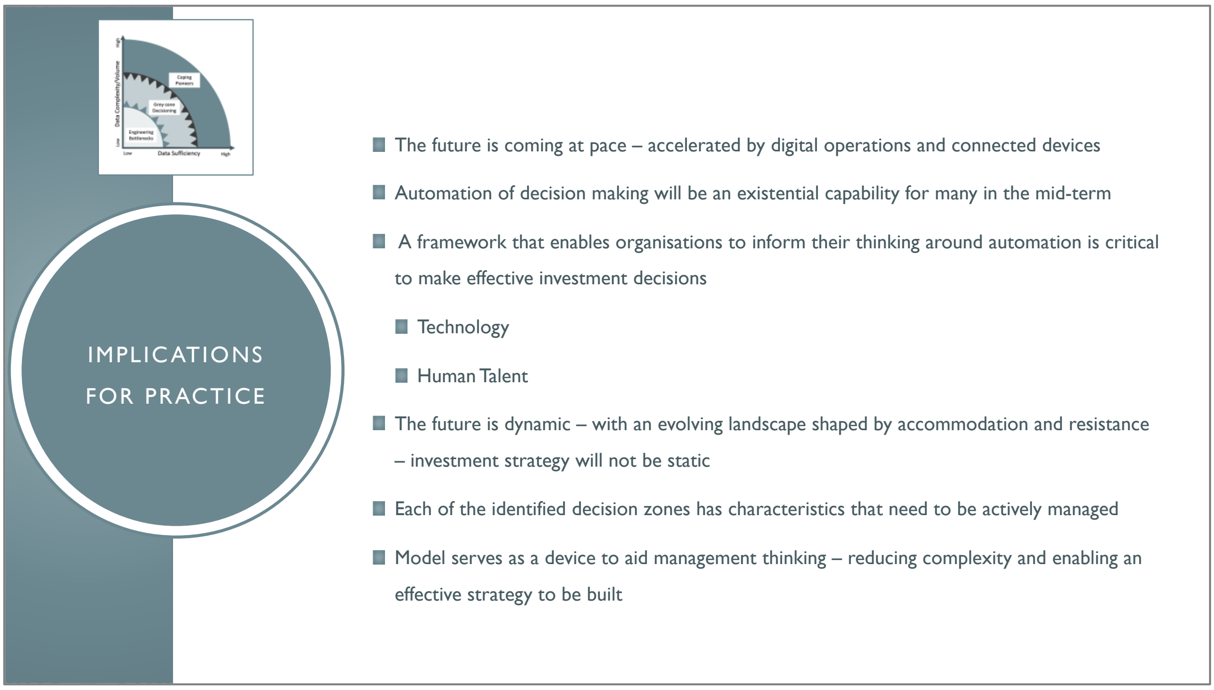


ACCELERATORS AND INHIBITORS

- Increasingly digital operations and connected devices are creating ever greater sources of data and complexity
- Connected devices, sensors and digital operations reducing the physical world to bits and bytes
- This burgeoning data source creates situations where machines become coping pioneers
- Accelerates the growth of third decision zone at expense of grey zone

- Regulators are both accommodating and resisting automation – boundaries clarify near-term limits – encourages conservative organisations
- Customers both accommodating and resisting - convenience versus quality trade-offs
- Professional bodies defending professions
- What is clear is that many drivers are now external to an organization.- fundamental shift

Slide 10


High
Data Complexity/Volume
Low
Coping Pioneers
Grey-zone Decisioning
Engineering Bottlenecks
Low
Data Sufficiency
High
IMPLICATIONS FOR PRACTICE
The future is coming at pace – accelerated by digital operations and connected devices
Automation of decision making will be an existential capability for many in the mid-term
A framework that enables organisations to inform their thinking around automation is critical to make effective investment decisions
Technology
Human Talent
The future is dynamic – with an evolving landscape shaped by accommodation and resistance – investment strategy will not be static
Each of the identified decision zones has characteristics that need to be actively managed
Model serves as a device to aid management thinking – reducing complexity and enabling an effective strategy to be built

Slide 11

Appendix V – Feedback Workshop Transcript

Attendees

- Simon Constance - Partner. Emerging Technology. Ernst & Young
- Fernando Lucini - Chief Data Scientist. Accenture
- David Feavearyear – DBA Student

Date of Workshop: Friday 4th November 2021 10:00 – 11:00

Method: Teams meeting – recorded and transcribed

[Small talk waiting for Simon to join]

David Feavearyear: Awesome. I think Simon is just joining.

Simon Constance: I'm sorry I'm a few minutes late. I was just trying to get someone to finish a call on time. Sorry.

David Feavearyear: No worries. Thank you.

David Feavearyear: Well, Simon, appreciate you joining.

So, thank you both very much. Before we get started. Are you both okay that I record this? I'll keep it anonymous[254]. But it just makes it much easier to transcribe and avoids taking loads of notes.

Simon Constance: Yeah.

Fernando Lucini: Hey, go, go, go.

David Feavearyear: Awesome - should we just do some quick introductions? You both know me, but I don't know whether you know each other?

Fernando Lucini: I think that's a sensible idea - nice to meet you, Simon. I'm the chief data scientist for Accenture globally. So, I run the global capability for data science - nice to meet you.

Simon Constance: Now that sounds like a cool job.

[254] Note: After reviewing transcript and lack of commercially sensitive information I write to request right to disclose participant's names – both consented in writing

Fernando Lucini: I'm not sure if it's cool. We can have a cup of coffee and discuss coolness of jobs in consulting!

Simon Constance: Brilliant. Oh, well, look, it may be that it just gives you an indication of what I do. So, I run our technology consulting practice across Europe, Middle East, India and Africa - looking at what we call intelligent automation. So that includes the use of AI as well as other automation tools from vendors like Microsoft and UIPath etc. - you'll know them all.

So, you know, we have quite a big team of data scientists.

I think it's a really interesting space. So, I think your job is cool.

Fernando Lucini: You and me alone!

No, no - joking aside. It is very glamorous in all directions. But it's an interesting time - I'll give you that.

Simon Constance: That's great.

David Feavearyear: That's awesome. Well, I guess that's a that's a nice segway then. So firstly, thank you very much for taking the time. I know you're both super busy. So, I really appreciate it!

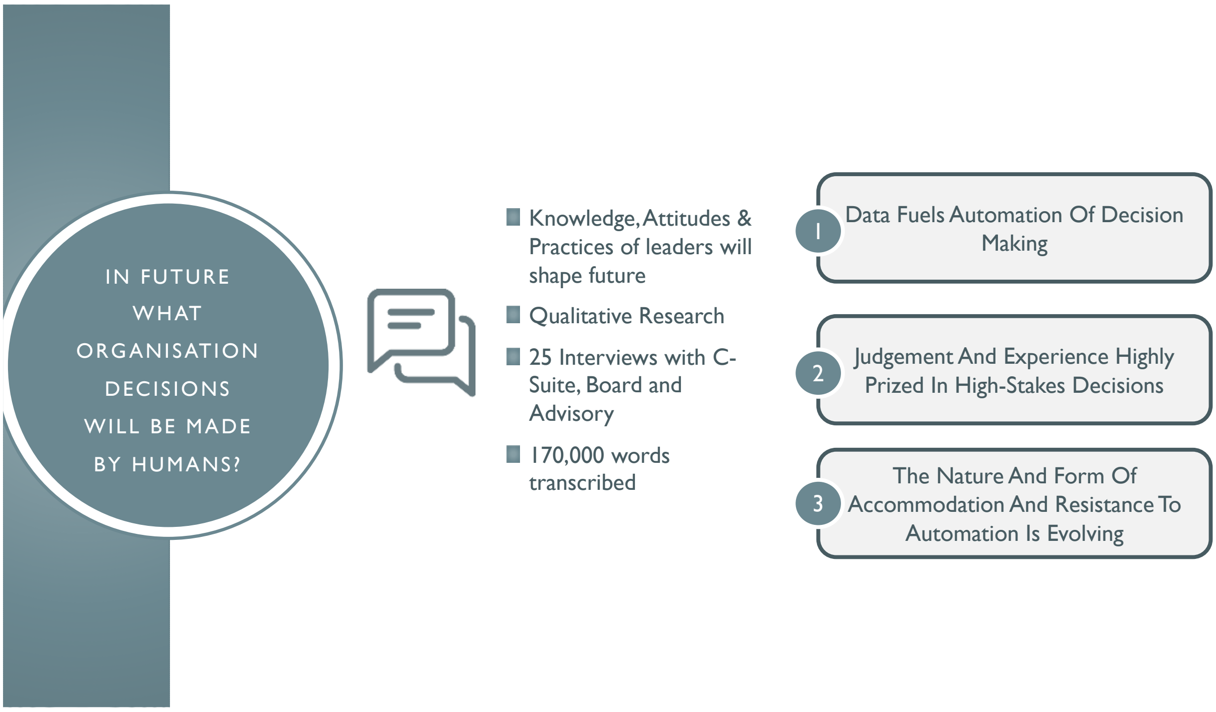
You both participated in the interviews I did earlier this year and I'm actually coming towards the end of this process now. One of the differentiators between a PhD and a DBA is that a DBA is intended to have real world impact and practical application, as it were. So, a PhD can be purely theoretical, but the idea of a DBA is that it helps practitioners as well as academics to think differently about the world in a practical sense.

I shared some slides with you in advance[255], but I wanted to walk you through a simple model that I built and get your perspective in terms of whether it's helpful, whether it resonates with you - and I guess as importantly - whether you think it would resonate with your teams and your clients as it were.

So, if it's okay with you, I'll speak for a few minutes, walk you through the model, and then the majority of the time I would love to get your feedback in terms of what you think and how useful, or otherwise, you think it might be.

[Slide below shared on screen]

[255] Full slide deck is set out in Appendix IV



So, I won't go through all of these slides in detail, but effectively my research was predominantly motivated by wanting to understand what organisational decisions in the future would be made by human beings and what organisation decisions would, or should be, made by machines. I took the view that the knowledge, attitude and practice of senior leaders will shape that future.

So, rather than doing a quantitative survey I wanted to get deeper into use cases and people's actual experience. So, I performed 25 interviews with the C-suite, board members and advisory firms such as yourselves. That resulted in 170,000 words of transcripts, which I dutifully made my way through and extracted what I considered to be the key themes.

To summarize what I think those themes are…

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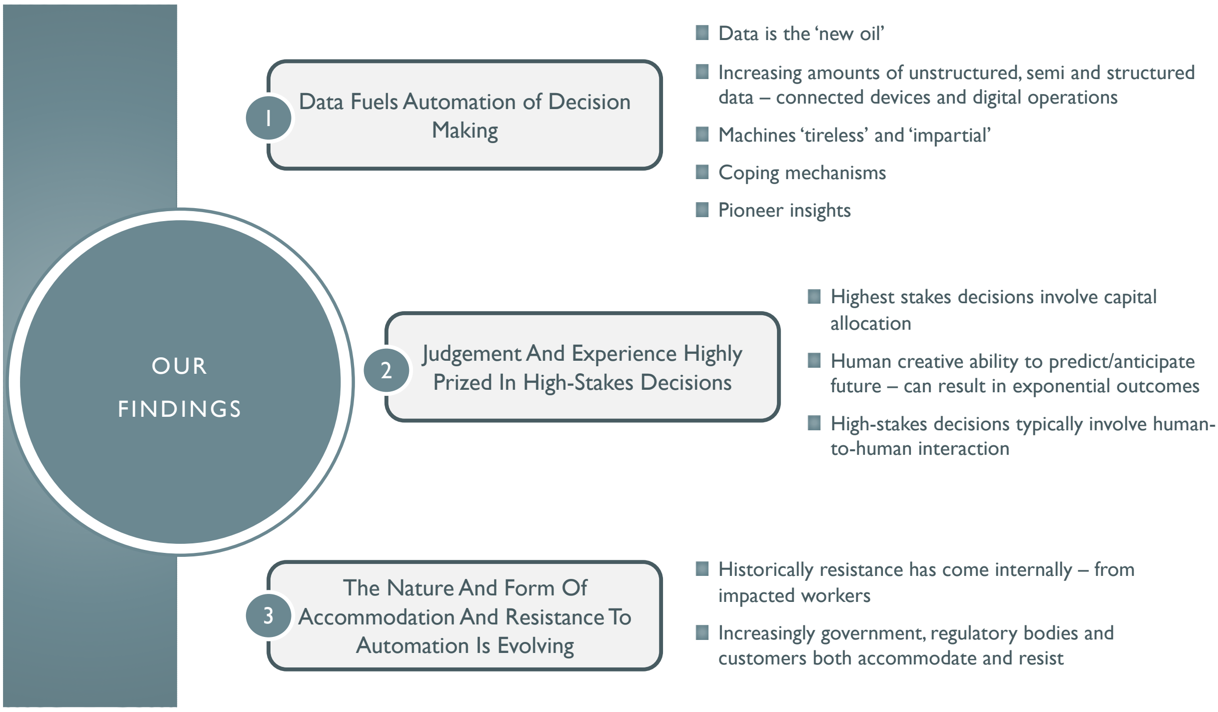


Some of these will feel like truisms for you, given what you do for a day job, but it's not necessarily intuitive for others that don't work in this space today.

So, I think the first thing to say is that data fuels the automation of decision making.

One person I spoke to described data as being the new oil. In its raw form it has limited value and is not of massive use, but once you start to refine it, it becomes really powerful.

We're also seeing increasing amounts of unstructured, semi-structured and structured data - and that's only increasing due to connected devices and increasingly digital operations. So, you're going to continue to see the amount of data grow exponentially.

Machines are obviously tireless and impartial and can run across vast data sets. As a consequence, for many organisations, machines become what I've described as coping mechanisms. So, they are a way of dealing with volume and complexity in a way that would be impractical if you just chucked human beings at the problem. And equally, they start to pioneer insights. So, they enable you to look across datasets and see trends that would be very difficult for even significant numbers of people to be able to discern.

The second theme that came out strongly, particularly when speaking to the board and senior leaders, was that actually human judgement and experience is still highly prized, particularly when it comes to high-stakes decisions. So particularly those that involve capital allocation, i.e. do I buy this company, do I not buy this company? Two related themes that came out were that human creativity is actually really quite important. So, our ability to be able to predict and anticipate the future in a non-linear manner can actually result in exponential outcomes.

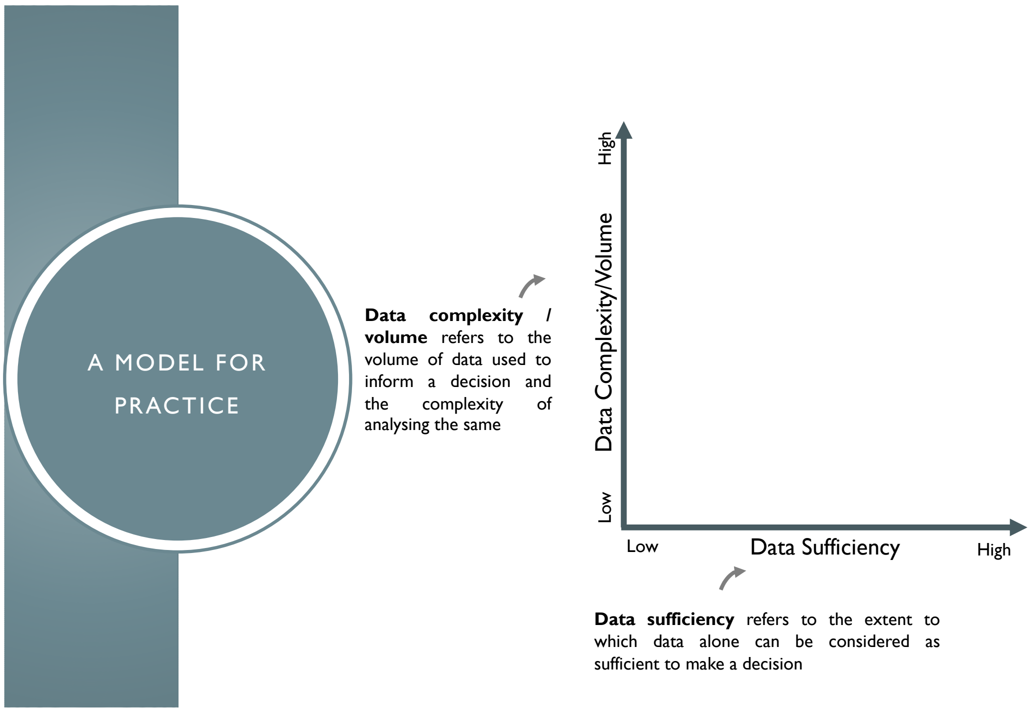
Equally, some of the highest-stakes decisions that are made involve a lot of human to human interactions that involve bringing people on a journey. So, you can make what seems to be a very good decision - but ultimately if people don't buy into it and you can't bring them on the journey, then that decision won't land in the organisation in the way that it might otherwise do.

The third thing that then came out was, and I thought this was quite interesting actually. Is that historically resistance has come from internal workers. So, as you introduce automation, people are displaced. You end up with human in the middle. And actually that's a source of resistance that results in unintended consequences. And you're not necessarily seeing the benefit you'd anticipated.

Increasingly, I think that dynamic is shifting outside of organisations. So, when you speak to leaders, they're talking more about government and regulation and what customers will accept and resist as being the key factors that are driving automation decisions. And I thought that was just quite an interesting thing to come out of this. Traditionally, companies can be quite insular in terms of where they think accommodation and resistance is going to come from. Actually, I think the world has moved on and companies are starting to look outside their boundaries.

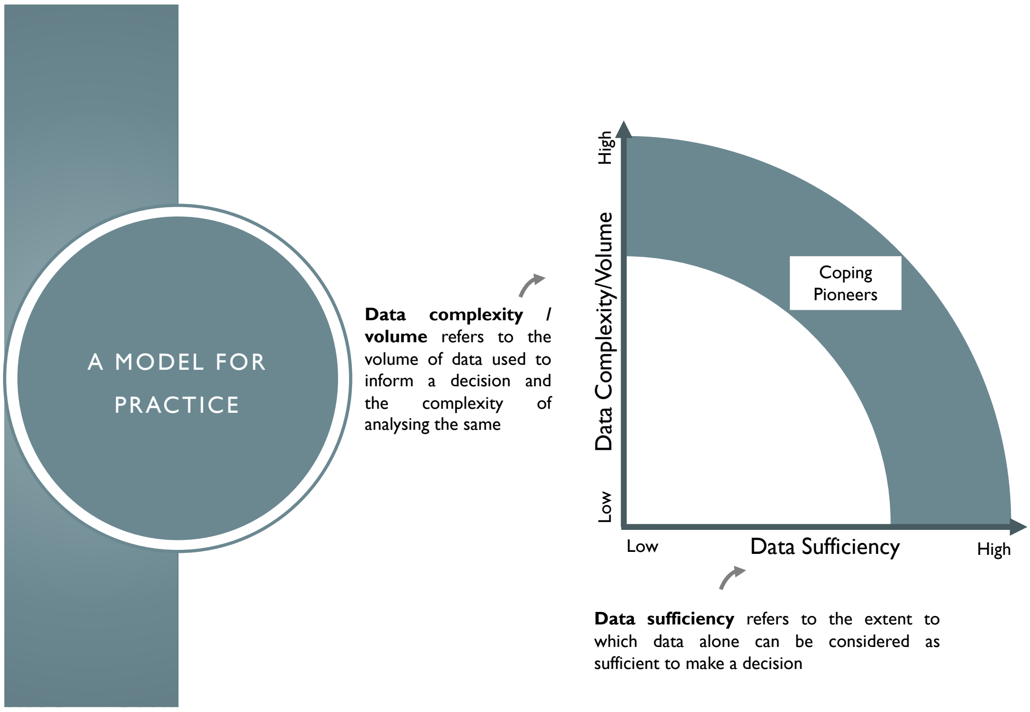
So, on the back of that, what I tried to do was to build out a model that would help people to contextualize what I've just described.

[Slide below shared on screen and animated through discussion]



The two axis revolve around data. So, one is about just the sheer complexity and volume of data itself and the other is around data sufficiency. So, by data sufficiency I mean the extent to which you can use data alone to make a decision.

[Slide animated as per graphic below]

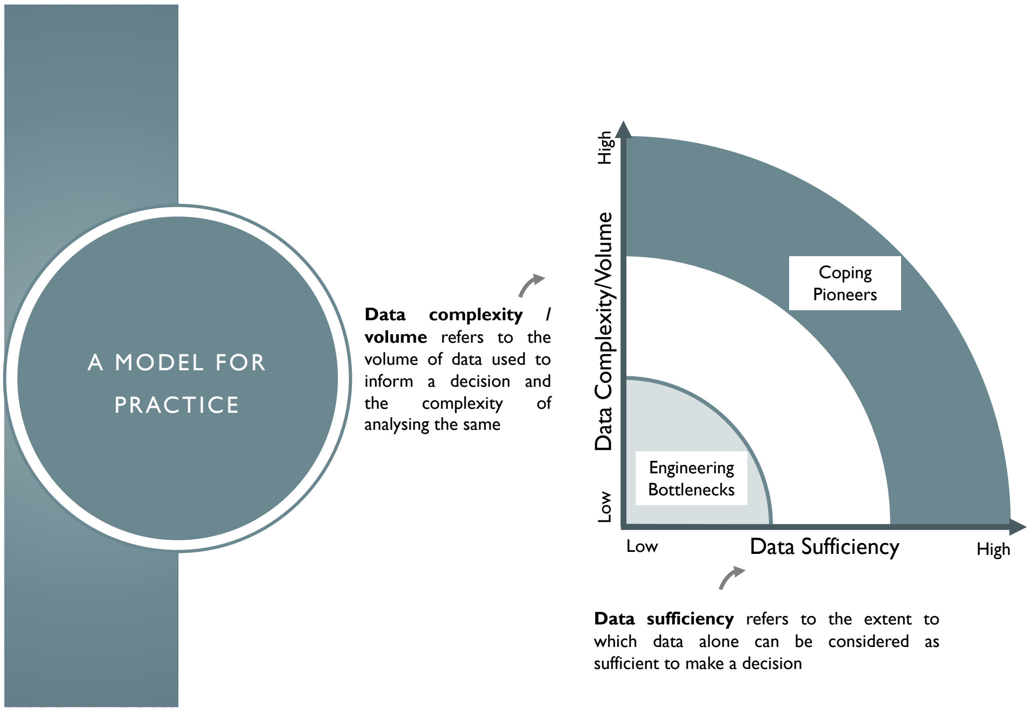


If you take situations where you have very high volumes of data and very high data sufficiency - so perfect example being credit decisions within high-street banking, as it were - machines are really well suited to deal with that complexity and volume - to make, you know, completely impartial, rational decisions, and as a consequence, in a bank, I would argue that credit decisions ought to be made by machines in 99.8% of situations. In such situations machines serve as coping mechanisms.

When you speak to financial services companies you also find that they are using machines to identify trends and data that human beings couldn't and that's enabling them to find new areas of value.

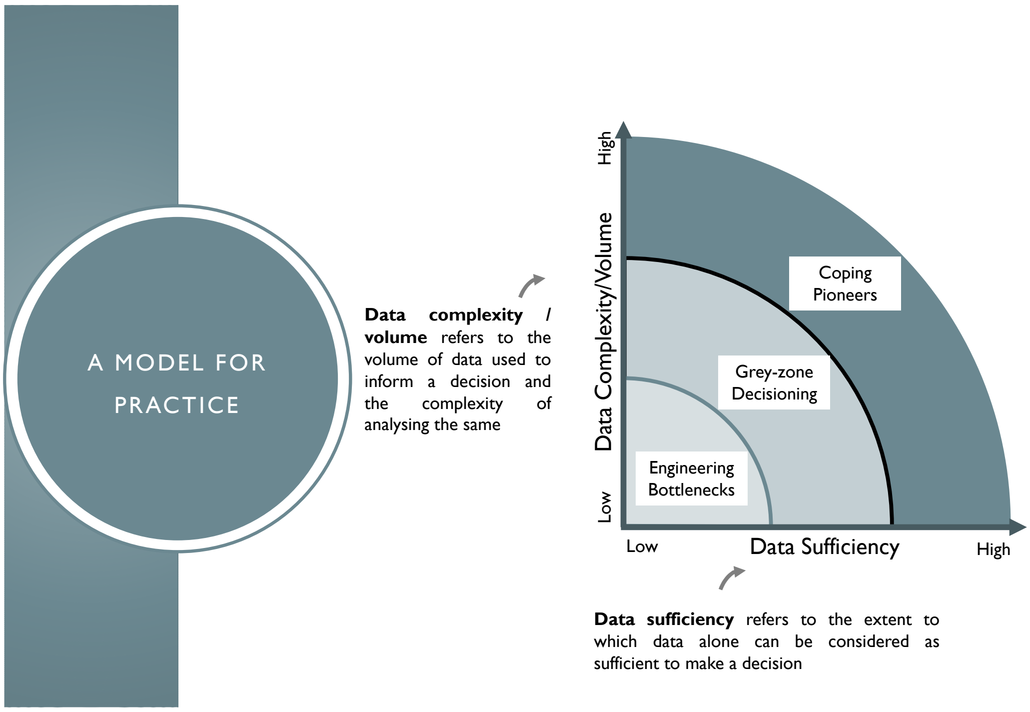
Machines therefore become what I've called coping pioneers.

[Slide animated as per graphic below]



At the other extreme, you've got what I've described as engineering bottlenecks, so these are areas that machines really struggle to get across. So, this is an area where judgement and experience are valued - that piece around things like mergers and acquisitions - the ability to predict, anticipate and think creatively about the future in a nonlinear manner. And I think M&A is the best example of a decision that would sit in that space.

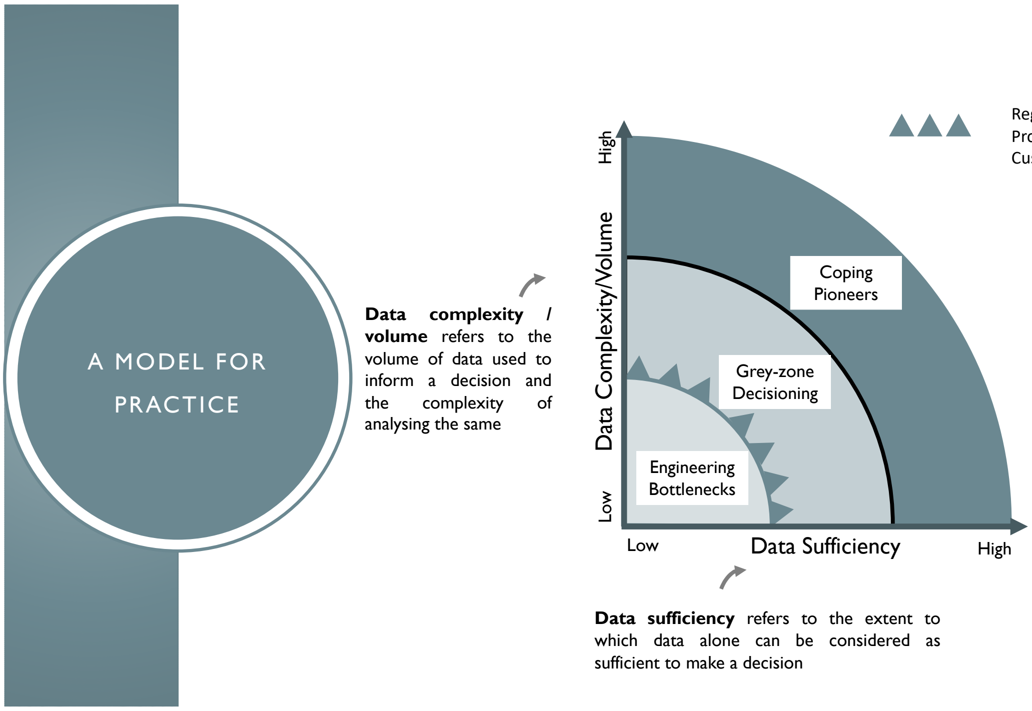
[Slide animated as per graphic below]



And then you've got what I've called Grey-zone decision making. So, this is where effectively you've got moderate amounts of data where effectively you end up with humans in the middle. And I think a really good example of this is a standard business case for acquiring a new customer. You have all the inputs in terms of what the costs are. You add your margin to it - but then you still have to determine what price you should offer that customer. It is the area where you get an intersection between humans and machines.

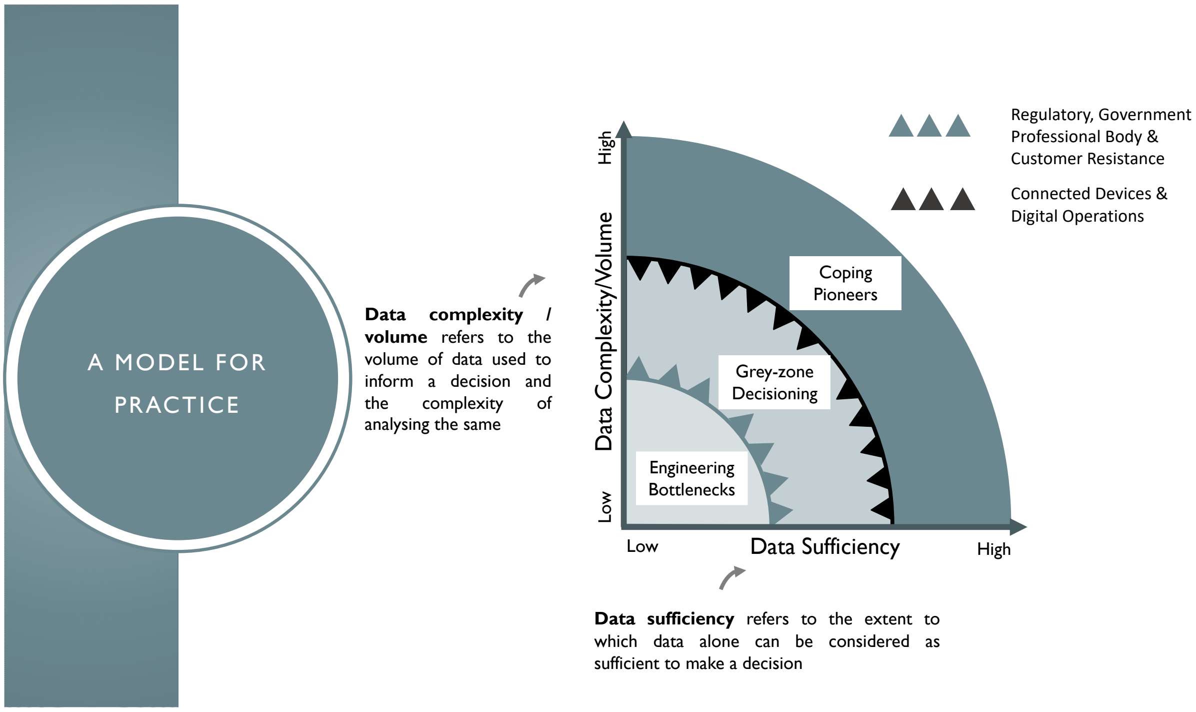
What you end up with here is potentially hundreds and thousands of individual use cases, and you can end up as a consequence with pilot paralysis if you're not careful. So, its important to determine where you invest your time and money.

[Slide animated as per graphic below]



This isn't a static model because, as I say, you've got changing attitudes from governments, professional bodies and customers, that both defends those human bottlenecks, but equally accommodates technology in certain instances.

[Slide animated as per graphic below]



And then you have connected devices and digital operations, which are effectively growing the amount of data and actually reducing the physical world to bits and bytes. And as you reduce the world bits and bytes, it becomes necessary for machines to serve in that coping pioneer role as it were.

So effectively this model has got three decision zones, together with inhibitors and accelerators.

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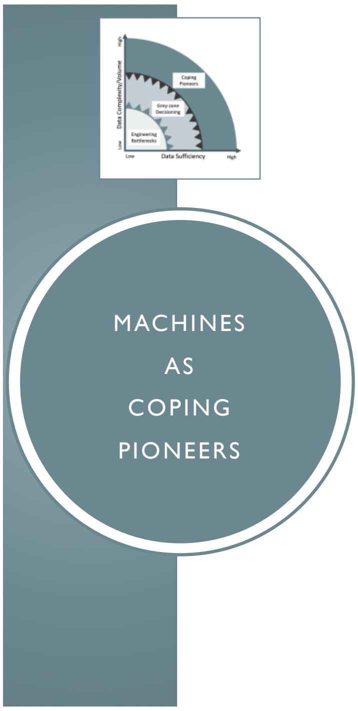


Decision Zone Characteristics	Automation Strategy	Considerations
Highly repeatable, hard decision processes at scale High volumes of data (structured, semi-structured and unstructured)	Machines deployed as coping strategy Machines used to pioneer ways to exploit data Data democracy enabled Limit/eliminate human decision making	Machine learning necessary to maximise value Machines will displace human agents Closed loop processes may enable zero touch or lights out processes Competitive advantage if early adopter Competitive necessity if early follower Robust data strategy required to collect and exploit data

Decision Example: Credit decisions in financial services. Decisions are highly repeatable and largely data driven, closed loop processes. Whilst exceptions may apply – vast majority of decisions will be automated enabling organisation to cope with complexity.

And what I've attempted to then do for each of these decisions zones is just set out the automation characteristics, that determine whether a decision sits in one of these three areas, the automation strategy that organisations should be thinking about and then some of the considerations that play into that automation strategy.

So, if you take machines as coping pioneers, for example. If you're an early adopter, it's a competitive advantage. If you're a follower, it becomes a competitive necessity. So, some of these things will become existential for organisations over time. I've done that across each of the three decision zones.

Clearly this model is never going to give people definitive answers. In the same way as if you look at something like Porter's five forces, it's not gonna give you the answer. But what I'm hoping it does is to serve as a device to aid management thinking. So, reducing what seems to be quite a complex area to something that's relatively easy for people to wrap their head around at various different levels and facilitate a conversation that enables decisions around automation strategy to be made effectively.

And with that, I'll shut up and I'd love to get your feedback.

Fernando Lucini: No, no problem at all. Simon, do you want to start? I can start otherwise.

Simon Constance: No, I suspect you've got loads of good stuff - crack on Fernando.

Fernando Lucini: Well, I'm sure we'll have some fun with it.

A couple of things.

Careful with the oil analogy, be very careful. Just be super careful. I'm sure Simon agrees. Use electricity. It's easier. Nobody's gonna grumble. Nobody's gonna shout at you. No bleeding hearts are gonna scream at you. And the truth is that it's a better analogy - because it’s something we manufacture versus oil, which is something we don't manufacture, we extract, right. It also helps because the idea of the of…

Simon Constance: Yeah, yeah.

Fernando Lucini: How we distribute electricity, how messy it is. It's all over the place. All the layers that you gotta deal with to store it, and then it's more akin to the problem of the data in an average company than oil, which is actually quite simple, you pump it out, you shove it over there, you refine it and you send it to the shop.

So careful with that one because I don't know, Simon, if you noticed it as well. We get shouted all the time. Anybody that's you know ‘data is like a new oil’ -   we hear ‘hold on, we don't want more oil.’

Simon Constance: I think you can, you can sort of live with it - yeah, yeah, yeah, I get it right - oils a bad thing - we're trying to get rid of it. But then I think the most important point for me that Fernando is making is that the characteristics of data are better suited to being described through the electricity analogy.

It's actually quite a lazy analogy to call it oil.

Fernando Lucini: Yeah.

Simon Constance: Because it you know, it underplays all of the real-world annoying problems that you find when you try and deal with data and which actually your model illuminates.

Fernando Lucini: Exactly another interesting one is...

David Feavearyear: I really appreciate that because I would never have thought about the political and environmental connotations associated. So, thank you.

Fernando Lucini: The scars. We all have scars - right, Simon? From analogies.

Another interesting thing to think about is value, the molecular value of data. It is not the same. The value of a piece of information about Simon or myself or you buying some gasoline in the BP gas station over there has effectively a minute amount of value as an electron of data, right, versus the same size of data at GCHQ – which is massively important because it can lead to a terrorist attack.

So, there is the idea that not all data has the same value to all people and the way I tend to talk about it is - if you read Harari's philosophy – he says that the value of data is the question of our time.

David Feavearyear: Yes.

Fernando Lucini: You could do an entire PhD on that - but the truth is that there is different value to different types of data. So, in your nice model, you act in different ways, if money is no object. At GCHQ, you must get all data – because no matter how small the data is and no matter how scarce it is in your model, I don't care if it's just one tweet. I must be able to do something about it – right. Versus hey, I've got a billion records coming in from a telco and I'm trying to extract value from a very small amounts of signals from a very large field.

I think there's an economic model there that I think is important. So be careful with the value of data you haven't touched on it as a thing and it's a different axis.

Fernando Lucini: The other note I made is you've said that machines will not give us creativity. Double down on that. Machines are not gonna do creativity.

Period. Not gonna happen. Anybody that says it is – it's not going to happen. It's fake creativity. It's not the human creativity that comes from the interconnectivity of everything we see. It's just not there. But it connects to your point on judgement, which is another absolute truth, which is that machines can inform judgement. They cannot replace judgement.

At the end of the day you can't really replace your judgement and give it to a machine, except in places like you describe - in things which are very transactional. The factors are very easy to explain. But if you connect, if you connect that to, to creativity and there are other studies you can read where you can see the core aspects of humanity and they're very difficult to replicate.

Simon Constance: Sorry, Fernando. Maybe I'll just build off that.

So, the point you're making now - I would just build on around the concept of the evaluation of the quality of the decision, right. So, your model doesn't reflect the quality of the decision. So, was it the right decision or not? Now that's a retrospective evaluation, right?

And maybe your model isn't trying to get to that, but knowing whether you are in the Grey zone or a coping pioneer is in part, you know, well ultimately, is decided by did you make the right decision?

What are the implications of saying that for your model? Well, the implications of that are there's some sort of feedback loop - you know. You talked about this notion of the model not being static. There's some sort of feedback loop in all of that, so if you look at the coping pioneers, if you look at the credit decision right. You know, Fernando you will have been involved in projects with clients over the last five years. Probably a bit longer in this space. We saw a massive take off in this particular space - when the banks were getting, the UK banks in particular, were getting turned over by the government for miss-selling of credit products, right. And there's been about three different waves of that and it just was impossible. They couldn't deal with it without doing exactly what you've said. It really was true that this was about 5 to 7 or 8 years ago now it really embedded the use of the tools you're talking about. Even in those banks that were initially a little bit resistant.

But the point is - as that work from seven or eight years ago evolved. It got better and better and better because people learned about the quality of the decisions they were making. And the coping pioneer of your model, the outer arc moved further down as a result of what was possible. So, there is something about the quality of decisions that shifts and advances the arcs in your model. I think that's worth talking about.

David Feavearyear: That makes perfect sense.

Fernando Lucini: Yeah, I'd, I'd agree. It's an interesting thing. Yeah. Quality. Yeah, absolutely. It's not just the decision – it's the quality of it.

You can also talk about the humanity of it – which sounds like its unmeasurable. But which is measurable. It's measurable. As simple as that. Empathy and all these other things that we require, depending on the type of decision.

Fernando Lucini: Now another one I had is. I think you've covered it. But it's always a problem of change more than it is a problem with technology - because the technology wick has been lit. It's a wildfire. So, you don't have to worry about the technology happening – it's going bonkers.

Every year, the numbers of papers we see are things like NIPS, which is the big scientific conference is growing.

And yet the amount of work that's done regarding change is light - so the side of you know 'what's my role in all of this?' And 'I don't know what I'm gonna do. What are you gonna do? What's Simon gonna do?' It feels like it's not there.

The truth is, when people do it well, it's because they change well. Not because they've got amazing technology - but because they've changed well. And then the technology is obviously underneath.

So, I would absolutely double down on that point of change. Trust is the key to using any of this, which leads to all these other things that come with it, right.

Simon Constance: Yeah, that's exactly what I was going to pick up on.

Trust - also takes you into understanding of being a competent user of decisions made using this technology, right?

And you know, you can, I mean we've all got so familiar with using ERP systems in our workplace, right? We don't even think about it. We're now at a point of trust in the underlying system that you don't need to think about where it's drawings data from. Are the master data sets accurate etcetera, etcetera. But I remember when these systems were really just taking off and I was just joining the workforce. You know, people did spend a lot of time questioning where did this data come from? This is because often it wasn't accurate and the processing of it wasn't always undertaken in the way that you were expecting it to be.

But these days, most of that's been ironed out, so this question of trust and being a competent user of these decisions, I think is a big part of this change journey. So, when we've done like these big contact center projects – I'm sure you've come across them Fernando, in banking, insurance, retailing - this stuff about recommending things to customers or next best action as it gets called. When this customer appears in my world, what should I do with them so it feels like an unprompted recommendation? It could be to go down another product line that they haven't touched, or actually to anticipate something that's gonna happen to them in the future - knowing that you've got a service that they would benefit from knowing about.

When we're rolling it out, having the users involved and actually down to quite junior contact center agents, right, who are taking calls, responding to web chats, sitting in branches of insurance companies where they have them still or banks. Having them involved in that change journey is just essential – and the success of doing that is I think, a practical reflection of what Fernando's just raised, which is you have trust and be a competent user – in order to then almost unconsciously, competently use the system in your decision making.

Simon Constance: I would just take that one step further into the regulatory and governmental space - you know, particularly in Europe. But you know more and more around the rest of the world is governments are pushing the question of trust and at corporate level trust becomes really important as a way of describing this competent user concept because there are societal equity questions around this – that governments feel they need to weigh in on, industry regulators feel they need to weigh in on, companies themselves, feel the need to weigh in on because it undermines their ability to use technology.

We have launched about a month ago, our own internal policy for anyone using data-driven decisions. Be it AI or other more simple models - in their work, right? It doesn't matter whether you're a specialist or whether you're frankly one of our M&A consultants who's trying to put together a deal book, you know, in a more automated way.

But actually our clients you know and other large corporates are doing that. General Motors are in the process of building that at the moment for themselves. They've talked to us, they've talked to other big companies like Accenture I guess. So, people are thinking about this stuff.

And again, the reason I think it's important and the reason to discuss it here is it, it changes your arcs and where they move on the basis of that.

Fernando Lucini: You know Simon, you're quite right. I use - I use a driving analogy when I talk to board because sometimes they don't get it, but it's, if you think about when we move from manual cars to automatic cars, right, the first time you get in the automatic car, you are pressing back the imaginary clutch for dear life. It doesn't exist. But every time you put your foot on the brake, your clutch leg is twitching, because you know your life depends on it.

As far as your body, your mind, the way you've worked up to then - that clutch pedal is critical to you not crashing. And it's a vestigial, it's a vestigial behavior. Such a simple thing remains a challenge for us, I don't know, Simon for you. But for me, it was years, looking about for the clutch pedal.

Imagine in a corporate environment where all your safety mechanisms - the things that tell you that you're gonna be okay. The things that tell you that you're not going to get fired. The things that tell you that everything is fine. They're all vestigial behaviours.

People tend to underplay it.

To Simon's point. Then you have, you know, companies like ours where I can't deliver anything without going through the AI ethics board. Nothing. Zero. I can't do it. And they don't try to stop me because they don't trust me - but because there's such a weight of vestigial behavior coming behind me - that without malice, it overrides all of the things that we need this technology to do and trust and work with. We need to create new behaviors, right.

And I tend to use that analogy and you get the whole 'ahhh – I get it.' Not that I'm saying boards are illiterate, but they're not far from illiterate! [All laugh]

Simon Constance: Well, yeah, but also the thing that they are uncomfortable hearing right - you know, to the conversation Fernando is talking about is - let's be clear that when we were making decisions purely as humans, right, without those arcs you're talking about. Our decisions weren't perfect right? It's just exactly as you say, Fernando, that weight of feeling and worry makes organisations uncomfortable unless a human has signed off on this decision or taken this decision, you know.

If you get refused credit… So, I've got someone that works for me - my housekeeper, and she obviously doesn't get paid a vast amount of money. She recently got turned down for a bank loan to buy a new car and she can't understand why.

It doesn't seem to me that she's a mad human being - but she's so angry with the bank for turning her down. Now, if any one of us reviewed their data model, we would say, well, that's a pretty sound model, right? It's based on a far deeper insight of customer behavior than any bank manager could have ever taken. But she feels because she can't appeal to a bank manager, she feels let down and angry, you know. She feels turned over in this decision and she's extremely grumpy. So, it's that.

That's the micro customer response, but at the board level they need to deal with the macro impact of those decisions and not get dragged into if you like pushing or shrinking the pioneer arc that you have - because there is a sense that the human decision-making process, for all of its qualities of creativity etcetera, etcetera, wasn't perfect in the first place.

Fernando Lucini: So, I extend my little analogy, this will make you laugh, Simon, because I go back and after I deliver the clutch thing - I go back and say 'by the way, if any of you think you're driving is wonderful, you must be smoking something.'

Simon Constance: Yeah, that's exactly right. Yeah. Yeah, yeah, that's exactly right.

Fernando Lucini: So, so the fact that my car, the little Volvo I have, which is not an expensive car, will actually swerve for me in the case of an emergency. I am deeply grateful for. Thank you very much. Because none of us are perfect. So, you can use analogies like that. But Simon's point is exactly right. We are holding technology to a standard that we're not meeting today. So, we're holding ourselves to a standard that doesn't exist today and it's protectionism, it is that vestigial behavior.

So, making your point on change – you should double down on.

That took me to my last point cause otherwise we will run out of time on your model.

There's a slight problem with your model. The picture of the model, not the model itself – which is totally fine. It is the picture, which is that if you look, if you look at the axis, you've got right, you've got the complexity and volume, which is totally fine, and the data sufficiency.

The bottom right is a place where machines do very badly. Really badly. Very small amounts of data. Bad.

Very small amount of data, bad very bad.

90% of all modelling in all companies the data is insufficient. 90% and I think I'm probably short – but 90% you find yourself in a place where the modelling you can do doesn't fit the volume of data and you do things like packing the data. There's techniques - but even then it's nonsense. So, in that space there's an element where you might wanna put like a safety box on there - which says well, the kind of decisions you could make on this are not very advanced.

Actually, somewhere in the middle where you have sufficient data and complexity - machines will do very well because they can deal with complexity in ways humans cannot.

But they need massive volumes for to deal with our complexity. It's simple maths. Lots of complexity, monsterous amounts of data - machines do amazingly. Not a lot of data and machines don't do very well. You know a lot of data, but you know, not a lot of complexity - you don't need that much advanced technology to deal with that. So there, there is a subtlety in that.

You gotta be careful with the type of automation you do. Notwithstanding things you can do with RPA, where what you are actually doing is simple RPA – where what you are doing is simple RPA – where you are making lots of data, simple data work for you. But in the in the complex knowledge-based decisions, you know judgement based decisions, you're not gonna get it except in one part of your model.

It is what it is.

Simon Constance: Yeah, yeah. And it goes back to this point about what's the right analogy for data? It’s why the point Fernando makes about electricity is so important, right? You know, so many organisations bump up against the gap between having the right data and having enough data to achieve what they want to do, right. They just don't right.

On all the big successful data projects that we could point to… Often the big decision-making projects or forecasting projects will often have a number of, for example, external data sources that are vast.

You know. Where they're pattern data sets, for example, insurance forecasting, risk forecasting - stuff like that, you know. Of course, there was a whole bunch of internal customer data that the corporate holds to put into the modelling, but actually you need those massive data sets as well - corporates just don't have them.

And then you also come to the implementation question. And you have to think differently about your business process to start getting it to generate digital outputs that can feed data models because a lot of business processes are set up to feed human decision making and human decision-making rests on things we see, things we read, you know, things we hear. The way we absorb information is different to the way a machine absorbs information. So, you end up having to put steps in processes to turn an input that a human can use into an input that an application, program or algorithm can use and I think that's something interesting.

It's another one of those slightly hidden mindset shifts. You might have a continuous improvement team in Pearson, for example. That's absolutely super-duper and full of black belts - but they're reengineering processes for humans to engage with. Actually, they need to reengineer processes for humans and digital decision making to occur.

David Feavearyear: That makes that makes perfect sense.

Fernando Lucini: Simon on that - I'm sure you deal with this everyday. You can't automate a bad process. A bad process is a bad process.

No automation will fix it. You're just gonna make it worse. You will drive yourself to madness. You'll think. 'Oh, the automation hasn't fixed it' – that's because it was a shit process to begin with - and you shouldn't have been using it.

That's a maxim as well. Simon's said it much better than I. But the decisions and the process we have as humans - sometimes work because the humans make them work.

The humans, you know, have the intelligence to wrangle the system and go call little Joey over there to give me that answer. You have to rethink the problem. Go back to first principles.

But before we're out of time, two quick ones. Firstly, time versus value.

Not all of the data that we have today is useful for tomorrow.

Data runs out of value, and especially with COVID, most of the data for customer analytics went down the toilet. Because it just, you know, the seasonality of it just went bonkers. So, there's a lot of things like reinforcement learning and clever things like that, that people are trying to use to create the answers of today because they can't use the data of the past. So, be careful with time versus value.

And the last one I'll give you on my list.

Oh sorry, it was the automation doesn't fix processes which we’ve talked about. But the time versus value is an important one. Super important. Simon you may see this as well – companies they think well, we’ve got 200 petabytes of data. Yeah okay, but how much of that is actually relevant?

David Feavearyear: Makes perfect sense. So, with the few minutes we have left.

Useful model, not useful model? Is it something that you could imagine people using in workshops or not - and be honest.

Fernando Lucini: I can tell you that I can send you 5 models like this that we use for consulting – focusing on strategy. They are very, very similar. And by the way, I don't mind sending them to you.

They come at it from a deeper perspective in terms of the industry they work in – so they are not as generic.

Your model is definitely useful – there is no doubt about it. The important thing is what actions you get out of it. What is the 1,2,3 that comes out of it.

Simon Constance: Yeah, yeah, look, I mean, I think the model is useful. It has to be because we've just had a very clear discussion based around it. That hasn't challenged the fundamental premise on which it's built, right. So, our discussion has been additive and explorative rather than questioning the fundamentals.

And look, you know, like all great things, it's simplicity is powerful. And you know, you can take this into a board discussion, right? And they'll get.

I do think the dimensions that we've all discussed this morning are really important to acknowledge because they drive the movement in the model and movement is powerful. As you say it's a dynamic model and being able to expand on the dynamism and what drives it is as useful as being able to show the categorization that it gives you.

I also think the last slide I was reading last night about implications for practice I think - I think those probably need another scrub through in the context of the type of discussion that we're having now. You could get even more pointy and specific about them.

You know when you talk about human talent, right? The human interaction is as you say it could be a whole PhD in its own right. So, I'm not trying to drag you down a black hole, but certainly there is a lot more to be said for that. It could be very specific.

The same with the technology and the limitations and that whole concept of data as electricity – unpacking that - has implications for implementation that are hidden and get lost. It's really easy for people at the board level to say well - ‘look at what the insurance industry does - we'll just do that in my industry, right?’ And that's the that's the space they operate in. Then you present them with your model and they go - ‘Oh, actually there's a bit more to this than I thought.’ And then if we can present them with a slightly deeper set of implications of the back of the conversation we've had and maybe others are having with you - then I think you get quite a powerful discussion on this subject.

David Feavearyear: Fabulous gents, I really, really appreciate the feedback and you taking the time! I know you are busy – so thank you!

Fernando Lucini: No worries and lovely to meet you, Simon. I'm sure we'll bump in the night in the world of consulting at some point.

Simon Constance: Yeah, yeah. I look forward to it. And if we're all in London, maybe, we can have a glass of wine some time. That might be a fun thing to do. Continue the discussion.

Fernando Lucini: That would be brilliant – maybe when you publish David. Let's celebrate your model.

Simon Constance: Yeah.

Fernando Lucini: Alright guys, have a good one. Bye.

David FeavearyearL Sounds good. Thanks very much, gents. Really appreciate it. Speak soon. Take care.

Simon Constance: Cheers both.

[End]

Appendix VI – Procurement Decisions

1.0	Supplier Selection	Volume / Complexity	Sufficiency
1.1	Does company have a preferred supplier?	High	High
1.2	Who should receive the tender documentation?	Low	Low
1.3	What questions should be included in the tender?	Moderate	Moderate
1.4	Has potential supplier signed an NDA?	Low	High
1.5	Who are company decision makers?	Low	Moderate
1.6	Who are supplier decision makers?	Low	Moderate
1.7	How does company assess responses?	Low	Moderate
1.8	Should company tender?	Low	Low

2.0	Supplier Onboarding	Volume / Complexity	Sufficiency
2.1	Is the supplier financially sound?	Moderate	High
2.2	Does the supplier have adequate insurance?	Low	High
2.3	Does the supplier operate in a sanctioned country?	Moderate	High
2.4	Does a conflict of interest exist?	High	Low
2.5	Does company already work with the supplier?	High	High
2.6	Does supplier have appropriate ESG credentials?	High	Moderate

3.0	Supplier Contracting	Volume / Complexity	Sufficiency
3.1	Does company already have a contract in place?	Moderate	High
3.2	Does company work from supplier or company terms?	Low	Low
3.3	Does company accept proposed revisions?	Moderate	Moderate
3.4	What counter revisions/proposals should company accept?	Moderate	Moderate
3.5	Where does company find best practice counter language?	Moderate	Moderate
3.6	Who in the company is empowered to make decision over proposed changes?	Low	High
3.7	How does company get the decision makers approval?	Low	High
3.8	Who is empowered to sign the contract?	Low	High
3.9	Where should the final contract be stored?	Low	High
3.10	What meta data needs to be collected from the agreement and where should it be stored?	Moderate	Moderate

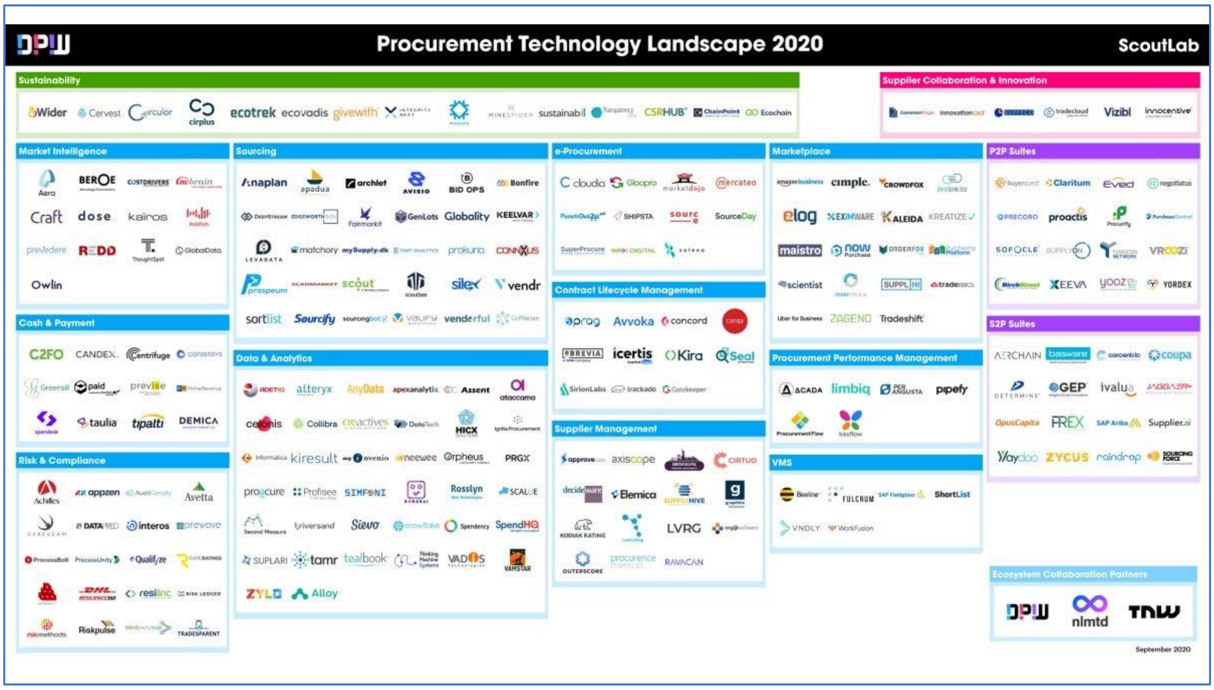
4.0	Issuing Order	Volume / Complexity	Sufficiency
4.1	Which system should be used to raise an order?	Low	High
4.2	Is order catalogue item or free text?	High	High
4.3	Who needs to approve the purchase request?	Moderate	High
4.4	How should the approval be sought?	High	High

4.5	Does the purchase request align with the purchase order?	High	High

5.0	Payment	Volume / Complexity	Sufficiency
5.1	Is the invoice received correct?	High	High
5.2	Has the company received the corresponding goods/services?	High	High
5.3	Does the invoice amount match the value on the PO and amount receipted?	High	High
5.4	Do the payment terms align to the contract?	High	High
5.5	Which cost centre should the invoice be charged to?	High	High
5.6	Do the suppliers bank details align to those on record?	High	High
5.7	How should the invoice be paid?	High	High
5.8	Should the invoice be cleared for payment?	High	High

6.0	Performance Management	Volume / Complexity	Sufficiency
6.1	Is supplier meeting its contracted obligations?	High	Moderate
6.2	Are SLAs / KPIs being met?	High	High
6.3	Are actions required to course correct?	Low	Low
6.4	Is escalation required?	Low	Low
6.5	Is a formal notification required?	Low	Low
6.6	Should company accept proposed remediation plan?	Low	Low

Appendix VII – Procurement Systems Landscape



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