A measurement model of value of data for decision-making in the digital era

Ganesh Sankaran*

Hochschule Furtwangen University,
Robert-Gerwig-Platz 1, 78120 Furtwangen, Germany
and
University of Plymouth,
Drake Circus, Plymouth, Devon PL4 8AA, UK
Email: gmsankaran@gmail.com
*Corresponding author

Martin Knahl and Guido Siestrup

Hochschule Furtwangen University,
Robert-Gerwig-Platz 1, 78120 Furtwangen, Germany
Email: knahl@hs-furtwangen.de
Email: guido.siestrup@hs-furtwangen.de

Ismini Vasileiou

De Montfort University,
The Gateway, Leicester, LE1 9BH, UK
Email: Ismini.vasileiou@dmu.ac.uk

Abstract: Despite burgeoning opportunities for data-driven decisions, research shows that decision makers are failing to make sense of data within a broader context of organisational change which presents the following pertinent questions: 1) How can decision makers measure the value of data by giving a holistic account?; 2) How should the organisation-specific blending of machine and human rationality be factored in the measurement model? This study tackles these questions by proposing a novel approach that combines system dynamics and the ability to incorporate data science methods. In addition to a conceptual description, this paper also describes a feasibility test conducted on a small-scale prototype set in a supply chain context. The results show that the use of sophisticated models that have a local scope ('locally rational') might have unintended global consequences. It underscores the need for a holistic model in the decision makers' toolkit providing the ability to run targeted simulations to assess digital investments.

Keywords: digital technologies; digital transformation; data-driven decisions; big data; quantifying value of data; bounded rationality; system dynamics; human-AI collaboration; supply chain management.

Reference to this paper should be made as follows: Sankaran, G., Knahl, M., Siestrup, G. and Vasileiou, I. (2021) 'A measurement model of value of data for decision-making in the digital era', *Int. J. Integrated Supply Management*, Vol. 14, No. 1, pp.50–76.

Biographical notes: Ganesh Sankaran is a PhD candidate at Plymouth University, UK, pursuing research on the value of data in a digital supply chain context. He is also a management consultant and a published author with over thirteen years of experience consulting multinational firms on designing and implementing supply chain planning systems.

Martin Knahl is currently an Associate Dean in the Faculty of Business Information System at Furtwangen University, Germany. He is a Research Fellow at the Centre for Security, Communications and Network Research (CSCAN) at Plymouth University. His research interests are in the areas of IT management and operation, internet governance, and distributed service development and utilization.

Guido Siestrup is a Professor for Business Administration and Logistics at Furtwangen University, Germany. He studied business administration in Bamberg and obtained his Doctoral degree at Bremen University. After starting his career in the industry, he became Head of the Department for Logistics and Production Planning at Dynamit Nobel France SAS and subsequently Divisional Managing Director for Logistics at Vest Wood Doors, Germany. In 2004, he was appointed Professor in the Faculty of Business Information Systems at Furtwangen University. His current research interests include the management of supply chain processes and closed-loop systems.

Ismini Vasileiou is an Associate Professor in Information Systems and Associate Head of School in the School of Computer Science and Informatics at De Montfort University, UK. Her research interests include social engineering, security education, big data, and technology-supported learning. She holds an EdD in Flexible Learning for Computing degrees in Higher Education, Senior Fellow of the Higher Education Academy and Fellow of BCS. She is publishing on topics including flexible learning, security education, and technology-supported delivery, and delivers a variety of invited presentations and keynote talks in relation to the above topics.

1 Introduction

The scale of some of the developments and the growth of data creation in the digital era is, quite literally, astronomical. According to estimates by the World Economic Forum, by 2020, there will be more bytes (44 zettabytes[1]) than there are stars in the observable universe (World Economic Forum, 2019). The digital transformation that has enabled this through the widespread adoption of digital technologies is the third IT-driven transformation[2] (Porter and Heppelmann, 2014) and represents the most significant shift yet in emphasis from systems/technology to data (Abbasi et al., 2016).

There are at least two ways to parse this shift. The first, an information-processing view, is a more general view that applies to any improvements to information technology, which gradually turns into "costs of doing business that must be paid by all but provides distinction to none" (Carr, 2003). In this view, organisations are information processors (Brynjolfsson and Hitt, 2000) trying to transform data and information into effective decisions. Thus, there is a sense that data is the fuel for the information processing engine. Combined with the notion that decision-making is the unifying construct of an organisation (March and Simon, 1993), the growth in significance of data falls out as an

obvious consequence of better opportunities for data creation and use afforded by a more powerful 'engine'.

A second way to parse the shift is specific to digital transformations. It requires paying attention to recent innovations that have drastically lowered the cost of processing power, storage, and connectivity components and have enabled widespread instrumentation, the culmination of which has led to new and creative ways of capturing data (McAfee and Brynjolfsson, 2012; Porter and Heppelmann, 2014). As a consequence, a synergistic relationship has emerged between data, and artificial intelligence and machine learning (AI/ML) algorithms, whereby improvements in one domain stoke more opportunities in the other domains. Therefore, the result of organisations "swimming in an expanding sea of data" (Davenport et al., 2012), coupled with hardware becoming democratised, has caused the focus of differentiation (to gain a competitive advantage) to shift significantly. The primary focus in the digital era is business processes (Hofmann and Reiner, 2006) powered by data and analytics, which Davenport (2006) had called one of the last remaining points of differentiation.

Thus, the claim that data is the 'decisive asset' of the digital age (Porter and Heppelmann, 2015) can be justified by its growth in prominence due to innovations in underlying technologies combined with its pivotal role in driving differentiation. However, for unlocking value from the data asset, and using its scarcity power to rise above the ubiquity of 'infrastructural' technologies (Carr, 2003; McAfee and Brynjolfsson, 2008), requires a unique configuration of complementary organisational assets (e.g., appropriate decision-making structures, management practices, and incentives) (Brynjolfsson and Milgrom, 2012).

In the digital context, complementarity is predicated on business-transformation focus rather than mere technology augmentation (e.g., Ross, 2017; Ross et al., 2017; Tabrizi et al., 2019; Weill and Woerner, 2018). That is, it involves recognising the difference between digital (a customer-centric value proposition) and digitisation (a technology-centric operational necessity) (Ross, 2017). From a data perspective, the right focus translates to its optimal use to ensure a fit between "what technology enables and what the marketplace wants" (Kavadias et al., 2016). However, achieving this fit is complicated by the nature of data which has itself transformed. A fact that is apparent in studies such as the one by LaValle et al. (2011) that show organisations struggling with abundant data and decision makers complaining that their organisations have 'more data than it knows how to use effectively'.

The nature of data, in this third iteration of IT-driven transformation, unlike in the previous instances, is fundamentally different, as it can influence events as they happen instead of just being used for analysis after the fact (that is after they end up as transactional data). In this sense, they are 'flows' rather than 'stocks' (Davenport et al., 2012). More broadly, most digital data differ along the dimensions of volume, velocity, variety and veracity – the so-called four Vs, which has led to the moniker 'big data' (McAfee and Brynjolfsson, 2012).

The transforming data landscape, characterised by big data as the currency of the digital economy, is mirrored in the attendant transformation of the decision-making landscape. Notably, there is a power shift from judgmental decisions to data-driven decisions (Galbraith, 2014). As a result, automation is no longer just restricted to routine tasks, where decisions are explicitly programmed and executed when triggered (Pomerol, 1997). It is also non-routine tasks that are being increasingly subject to automation with the help of AI/ML methods. Brynjolfsson and Mitchell (2017) note that Polanyi's

paradox that states 'we know more than we can tell', which constrains the range of tasks that can be automated, is being upended by novel algorithms capable of mimicking human reasoning. Therefore, generating insights from big data also raises the challenge of role delineation between humans and algorithms.

Despite broad acknowledgement in the research community and among practitioners of the 'disruptive' influence of big data characteristics on the interplay between data and organisational complementarities for value creation, there has not been sufficient research focus on some key topics (Abbasi et al., 2016). Abbasi et al. (2016), premising their arguments on big data's potential to 'significantly alter value chains' (value chains are the pathways of knowledge discovery and decision-making), review extant issues and chart a research agenda for closing the gap. Although grounded in information systems, their recommendations span a wide range of issues including, epistemological, methodological, design, and ethical.

Synthesising their analysis and recommendations on decision-making – the focus of this paper, and emphasising the importance of complementarities, two questions materialise. Namely:

1 How can decision makers measure the value of data by giving a valid account of its 'embeddedness' in a system of organisational complements, in other words, a holistic account?

2 Furthermore, given the rapidly shifting balance of power between intuition and algorithmic decision-making, how should the organisation-specific blending of a machine and human rationality be factored in the measurement model?

Answering these types of questions calls for the ability to quantify big data's role in decision-making that captures the organisation-specific mix of intuition and AI/ML, and that does so in the context of essential complementarities. Such a capability is currently lacking (Abbasi et al., 2016) and one which the model proposed in this paper seeks to address.

The proposed model is novel in the sense that it combines system theoretic principles (for a causal representation of the problem domain and to allow modelling of judgmental decisions), and AI/ML methods to enable studying the organisational-performance impact of data-driven decisions. Such a model treats data as an 'intervention' that precedes an interplay between human intuition and algorithms to generate decisions that impact performance. A more realistic causal representation of the problem also enables checking if locally rational decisions (that is, decisions in one functional area) cause overall dysfunctional behaviour (Glazer et al., 1992). Furthermore, the choice of the method allows simulation which, besides offering computational tractability, enables decision makers to run targeted experiments to assess investment decisions.

In addition to a conceptual description of the model and its principles, this paper also describes a feasibility test conducted on a small-scale prototype of the model using a toy problem, set in a supply chain context. It concludes with a discussion of the results and offers a roadmap for future research.

2 Literature review

Human judgment is under immense scrutiny in our current organisational decision-making environment where a combination of algorithms (powered by AI/ML) and data has given rise to ever-more situations where "authority is increasingly expressed algorithmically" (Pasquale, 2015 cited in Lindebaum et al., 2020). A key driver for the push for increased adoption of algorithms is an apparent dichotomy between human judgment and algorithms that rests on the idea of rationality with the implication that algorithms are "supercarriers of formal rationality" (Lindebaum et al., 2020).

On the question of the role of human decision makers in such an environment and on whether humans should cede control to algorithms as much as possible to make more rational decisions, historical developments in the field of rationality provide a useful starting point. The first section, therefore, describes how views on rationality have come to shape theories of decision-making and will frame the discussion on the extent to which perfect rationality is even possible, independent of the information processing medium (a human brain or a computer). It is followed by a review of the state-of-the-art of research into the role delineation between human judgment and algorithms.

Notwithstanding the relative contributions of humans and data-driven algorithms, proper utilisation of data requires the ability to sift through it and identify that which is informative or holds the most potential to drive insights and value. An inability to do so can, as several studies highlight, lead to lost opportunities with regards to data-driven decision-making (IDC, 2014; LaValle et al., 2011; McAfee and Brynjolfsson, 2012). Therefore, the final section reviews research contributions on the topic of measuring the value of data and motivates arguments for why there is a research gap that needs addressing.

2.1 Rationality in decision-making: insights from theory

Some of the earliest descriptions of rationality, a concept that has been around for several centuries, were linked to the idea of successful action – that is, reasoning about the most appropriate means to reach the desired ends. Aristotle called it practical reasoning, and in his mind, the ends were a given, and the focus was instead on the search for means that can 'easily and best' achieve the ends [Russell, (2019), p.21].

The conceptualisation of decision-making, which is as well a search (for information, until the marginal value equals the marginal cost of searching (Glazer et al., 1992), turns on assumptions regarding the rationality of the decision maker. Therefore, the various theories of decision-making can be categorised based on the degree of rationality they presume (on humans) into three groups: decision-making as exemplified by neoclassical economics and its adherents (such as decision analysis), behavioural economics, and bounded rationality. If placed along a spectrum of 'presumed human rationality', neoclassical economics sits near the 'humans are perfectly rational' end, behavioural economics near the 'humans are highly fallible' end, and bounded rationality occupies a spot between the two (and somewhat closer to neoclassical economics).

The neoclassical economics' view is one of the prototypical 'economic man' who epitomises rationality (Fox, 2015). The economic man is omniscient and can consider all alternatives, is not constrained by any cognitive limitations and can calculate all consequences, and has a consistent and coherent set of values to evaluate those consequences to make the rational choice.

Behavioural economics, which is as well a departure from the economic theory of rationality, however, takes a more nuanced view whereby humans are neither perfectly rational nor entirely driven by emotions (Kahneman, 2011).

Although behavioural economics purports to show rationality as exercised by humans in real-life to be fundamentally different from one espoused by economic theory, the biases and errors are still primarily measured using perfect rationality as the benchmark (Gigerenzer and Goldstein, 2011). That is 'errors' are, by definition, deviations from the norms of Bayesian statistics, expected utility, and consistent set of values – the conceptual underpinnings of perfect rationality (Fox, 2015).

Bounded rationality, a concept initially developed by Herbert Simon, differs from behavioural economics in that it views heuristics, which are a consequence of limited rationality, not as errors or a compromise, but as evolved strategies for making accurate inferences in real-world environments while simultaneously satisfying the "constraints of limited time, knowledge, and computational might" (Gigerenzer and Goldstein, 2011).

Accounting for such constraints sets bounded rationality apart from economic theory as well, which has as its objective 'optimisation'. Bounded rationality, on the other hand, searches for a satisfactory solution instead of an optimal solution. Therefore, the calculus of choice here is one of 'satisficing' (a term coined by Simon) and not optimisation [Simon, (1996), pp.27–29].

A satisfactory solution might seem like a compromise, despite a claim to the contrary that bounded rationality makes. However, real-world complexity and uncertainty (especially, randomness or aleatory uncertainty that cannot be quantified) imply optimisation in any real sense is neither achievable by humans nor by computers [Simon, (1996), pp.28–29]. In fact, under certain conditions, satisficing has been shown to perform better under less, rather than more information, demonstrating a 'less is more effect'. Gigerenzer, therefore argues that bounded rationality shows "models of inference do not have to forsake accuracy for simplicity" (Gigerenzer and Goldstein, 2011).

Making correct assumptions about human rationality is essential for modelling the decision-making schema of an organisation, which the model proposed in this paper seeks to do. The view that is adopted is one that is closest to bounded rationality. It is that humans are rational in intent, but in the face of uncertainty are limited in fully exercising their rationality due mainly to cognitive limitations and real-world constraints. It is also a view that agrees with the assessment of March (1978) who notes that "bounded rationality is a sensible adjustment to the costs and character of information gathering and processing."

2.2 Human judgment and algorithmic decision-making: state-of-the-art

Artificial intelligence (with machine learning), it has been noted, belongs to the same category of technological innovations as previous, similarly transformative, innovations such as electricity, the steam engine, telegraph, and internet (Brynjolfsson and McAfee, 2017). They are similar in the sense that they spawn other complementary innovations and generate opportunities such that they belong to a class of innovations known as general purpose technologies (GPT) (Brynjolfsson and Hitt, 2000). Although, experts note, there is a crucial difference (that is generating much interest in media and academic circles), one that has to do with the type of automation they enable and its impact on tasks humans perform and even entire occupations (Frank et al., 2019).

The model for task automation before AI/ML was one that McAfee and Brynjolfsson (2017, p.37) have termed the 'standard partnership', which restricted it to those tasks that can be clearly 'specified'. On the other hand, algorithms powered by AI/ML do not rely on explicit programming and possess the ability to learn (not unlike humans), which has opened up for automation tasks that are not necessarily articulable. It has led to AI/ML expanding their footprint into areas that have heretofore been the sole remit of humans, and with potentially enormous workforce implications (Frank et al., 2019).

An assessment of workforce implications, however, requires one to differentiate between the *mere ability to perform* a task and the ability to *perform it well*. Several studies pitting humans against algorithms have shown that performance of algorithms is beginning to match (Brynjolfsson and McAfee, 2017) and in some cases, surpass humans[3] in the areas of perception, cognition, and problem-solving. A key implication is that, besides job augmentation, there are more opportunities now for job substitution.

With these recent developments, scrutiny has further intensified on the role of human judgment. The question of role delineation has acquired greater relevance because of the debate around the need for theory. Some experts have argued that algorithms fed from a 'fire hose of data' can learn from statistical correlations [McAfee and Brynjolfsson, (2017), p.46] and can be 'theory-free' (Anderson, 2008; Harford, 2014). The idea of theory-free models has received traction through some high-profile studies involving the prediction of seasonal flu (Harford, 2014), and housing prices [McAfee and Brynjolfsson, (2017), p.38]. These studies have relied on Google Trends, which does not understand causal relations but purely works off of observational data.

However, the initial enthusiasm for theory-free, fully autonomous models, has tempered recently [for reference, the influential article proclaiming the 'end of theory' was published in 2008 (Anderson, 2008)]. There are several reasons for it.

Firstly, after initial successes, flu trends had a reckoning when correlations between a search for flu-related terms and incidences started to become spurious (e.g., due to media coverage about flu triggering searches). It led to actual incidences becoming uncoupled, exposing the fragility of the predictions.

Secondly, there has been a renewed interest in causality, leading to pushback on a theory-free approach, in the AI/ML research community. Breakthroughs in research on Causal Inference and Structured Causal Modelling pioneered by Judea Pearl and others, stressing the importance of 'explanatory' models to algorithms, have been significant contributors (Pearl and Mackenzie, 2018; Schölkopf, 2019).

Finally, from a decision-making standpoint, there is a broad consensus that human judgment still has a role to play along several dimensions. Perhaps the most critical dimension is values (or preferences); because there is no clear separation between preferences and the process of decision-making, it calls for human judgment to untangle facts from values [Simon, (1997), pp.68–71].

2.2.1 Decision-making under systemic risks

A perspective that has significant implications for the relative importance of human judgment and autonomous decision-making, and one that is in the spotlight with the recent COVID-19 pandemic, is of systemic risks. In contrast to mere risks, systemic risks generate cascading failures in strongly-coupled systems where assumptions of independence between systems do not hold, leading to systemic instability (Helbing, 2013).

In the current pandemic, several global supply chains are experiencing the disastrous effects of systemic risks, and the situation has been made worse due to the presence of highly interlinked supply networks (Ivanov and Dolgui, 2020). The dense networks and the reduced friction in their numerous pathways have enabled dangerous events to "spread rapidly and globally" (Helbing, 2013) highlighting one downside to the many beneficial effects of globalisation and digital technologies.

The impact has been especially severe for supply chains that are not tightly coordinated as the ripple effects of supply disruption are more acute in such cases. A key reason being lack of coordinated decisions leads to downstream nodes ignoring the supply line and continuing to place orders causing the compounding of the ripple effects (Dolgui et al., 2020; Scheibe and Blackhurst, 2018).

More broadly, effective decision-making under systemic risks where extreme events are no longer rare, call for a combination of proactive and reactive strategies (Dolgui et al., 2020). An essential proactive strategy involves making design choices that enable looser coupling of systems to mitigate failure-cascades and factoring in redundancies (Helbing, 2013; Ivanov et al., 2019). A corresponding reactive strategy capitalises on the design choices by emphasising decentralised coordination as opposed to a top-down approach as the principle of self-organisation is one that is known to be resilient to perturbations (Helbing 2013). The reactive strategy must also give credence to the fact that the assumption of history being a good indicator of the future becomes mostly invalid, and historical data, as well as algorithms that rely on them, lose credibility. However, this is not universally true. For instance, in a pandemic, real-time data sources such as location data and medical data can enable tracing of people who have come in contact with infected persons so that they can be alerted (Jordan and Mitchell, 2015).

The discussion highlights that besides value judgment, there are other judgmental factors to consider, as well. These factors, such as choice of methods, choice of data sources, feasibility assessment, and implementation strategies (Hogarth and Makridakis, 1981), take on a much greater significance in the presence of systemic risks. The extent of judgmental input in the decision-making process also depends crucially on the significance of the decision. The hierarchy-of-decisions conceptualisation (Silver et al., 1998) is useful here. The lower-level decisions along the hierarchy (more execution-oriented, of lower strategic significance) tend to be closed in terms of variables to consider. As a result, they are more amenable to automation via algorithms as there is considerable structural inertia at play (Hogarth and Makridakis, 1981).

In sum, despite significant advances in algorithmic decision-making, there is a consensus emerging of a continuing need for collaboration between humans and AI/ML (Barro and Davenport, 2019; Duan et al., 2019; Saenz et al., 2020). The extent of collaboration will depend on the specific organisational configuration, complementarities, and risks and requires a model of its decision-making schema (Grimmer, 2015).

2.3 Measuring the value of data

The process of decision-making provides intuition about the link between data and value. Decision makers use information about the state of the world and compare them with their goals to ascertain differences and enact actions that in their view move the world towards the desired state [Sterman, (2000), p.15]. Hence, the measure of value is a function of the effectiveness of decisions and actions that proceed from it.

For a more formal link, there are several theories that one can appeal to such as Blackwell's state of nature, information processing theory, information theory, information value theory, information economics, and resource-based view theory. Despite the diversity of viewpoints, the theories fall into two broad categories based on whether the information is considered purely in the probabilistic sense or whether the economic consequences factor in the calculation. For example, Blackwell's theory is a purely probabilistic construct (Bielinska-Kwapisz, 2003). That is, two events having the same probability are numerically equivalent in an informational sense. Information theory (pioneered by Shannon) aligns with this. Howard's 'information value theory' (Howard 1966), on the other hand, extends the information theory by giving due consideration to the economic value of reducing or eliminating uncertainty, which is termed 'value of clairvoyance'. The theories of information economics, and resource-based view theory, albeit less mathematically formal, belong in this category. This paper adopts the latter view whereby value assessment is in terms of performance metrics which in turn have a financial impact.

On the question of what makes for a truly successful digital transformation – the foundation for data-driven decisions, there seems to be a consensus among scholars. It is that certain complementarities need to be present and that they should transcend technology to include various management practices to ensure a fit between technological capabilities and market needs (Kavadias et al., 2016; Ross et al., 2017). For instance, complementarities can range from reconfiguring organisational resources such as information sharing practices (Woehner et al., 2013) and decision-making rights that favour fast decisions (Mendelson and Pillai, 1999; Tambe et al., 2012), appropriate management practices around process, performance, and customer management (Mithas et al., 2011), and creating or reconfiguring inter-organisational networks that take into consideration changes to transaction cost economics in the presence of enabling technologies (Mendelson and Pillai, 1999).

The literature on complementarities often draws on principles from resource-based view theory that holds that creating and sustaining competitive advantage requires configuring organisational resources in a way that confers value, inimitability, non-substitutability and rarity (Melville et al., 2004). Therefore, for organisations that fall short of expectations with regards to data-driven decisions, the obstacle is often not technology, but a failure to properly embed their information assets in a system of complements (LaValle et al., 2011). On the other hand, for organisations that do manage to find the right combination of practices to amplify the impact of data-driven decisions, the impact is felt across a range of performance metrics such as productivity, asset utilisation, profitability, and customer satisfaction (Brynjolfsson et al., 2011; Ross et al., 2017; Wamba et al., 2017; Akter et al., 2016). Unfortunately, research shows that such organisations are few and that there is a significant performance gap between leaders and laggards (LaValle et al., 2011; Weill and Woerner, 2018; Westerman et al., 2014).

For instance, an empirical study of 330 public North American companies has up to 32% of the respondents rating themselves three or lower on a five-point scale on their utilisation of data for decision-making (McAfee and Brynjolfsson, 2012). In a global survey of 3,000 stakeholders spanning more than 30 industries, the leading obstacle to achieving better performance was the lack of understanding of how to apply analytics to decision-making (LaValle et al., 2011). Another empirical study of around

400 enterprises embarked on a digital transformation journey hints at a plausible cause underlying poor performance. In this study, enterprises were rated along dimensions of operational efficiency and customer experience. It was found that those that performed the worst (51% of those surveyed) and were placed in the bottom-left quadrant, suffered from 'silos and complexity' and their profit margins averaged five percentage points below the industry average. In other words, a fragmented approach resulted in poor performance and a "complex landscape of processes, systems and data" (Weill and Woerner, 2018). A further illustration of organisations failing to find the right fit is the fact that an estimated 70% of the spend on digital transformations in 2018 ($900 billion out of a total spend of $1.3 trillion) did not achieve expected results (Tabrizi et al., 2019).

The above examples seem to fit into a familiar theme – of decision makers failing to make sense of data within a broader context of organisational change that is an integral part of every digital transformation. Ross et al. (2013), based on their research on business value from big data, report that the most common reason for failed investments is not knowing how to manage and analyse data to gain understanding and generate insights that guide profitable outcomes. It appears that decision makers are struggling with putting into practice one of the core tenets of data-driven decisions, which is finding 'informative' data within a large body of data (Provost and Fawcett, 2013). It gives further credence to the call of Abbasi et al. (2016) for more research on the impact of big data characteristics on the information value chain.

Reviewing existing research on quantitative models [that have explanatory power, as elaborated in Bertrand and Fransoo (2002) which have attempted to model reality more holistically], one does find relevant examples (e.g., Lyneis, 2000; Vlachos et al., 2007). However, such models exclusively use simple heuristics and neither consider big data characteristics nor provide the ability to represent a decision-schema that combines heuristics and AI/ML algorithms – a gap the model proposed in this paper aims to address.

3 Proposed quantitative model

3.1 Design prerequisites

The preceding discussion has laid out a case for a model, which decision makers can utilise, to navigate an environment of abundant data effectively. The arguments made stipulate specific requirements for such a model.

An evaluation of 'informativeness' is predicated on a valid account of the interconnectedness of assets. From a decision-making perspective, as argued, digital organisations for the foreseeable future must contend with a blend of strategies that combine human intuition and algorithmic decision-making. It also trivially follows from the argument about complementarities that the measure of value differs across organisations. That is, the notion of insights-laden data is not generalisable; therefore, it becomes crucial to quantify data's impact on an organisation's outcomes (through an organisation-specific set of efficiency and effectiveness metrics).

Condensing the above prerequisites leads to three postulates that inform the search for a suitable design for the model:

1 the ability to evaluate in a system of organisation-specific complementarities (*holistic*)

2 the ability to support a blend of decision-making strategies that combine human intuition and AI/ML methods (*blended rationality*)

3 the ability to quantify value in terms of relevant outcome metrics (*quantitative*).

3.2 Design decisions

To move from the conceptual idea of a holistic model to concrete design principles, it helps to consider a term closely aligned with complementarity – synergy. Synergy, whose essence, often summarised as 'the whole is greater than the sum of its parts', is the primary mechanism that makes implementing technology, especially one that's as pervasive as digital, fraught with risks of failure. For example, in an organisation undergoing digital transformation with an incumbent set of complementary practices, change that just focuses on one or a subset of those practices can lead to reduced performance. Furthermore, as there is an innumerable combination of (plausible) practices, there are multiple local maxima, leading to a so-called 'rugged landscape' (due to a discontinuous payoff function), complicating the search for a successful strategy (Brynjolfsson and Milgrom 2012).

Therefore, for holistic modelling, data must be evaluated in an organisational context that is not merely an assemblage of parts, but a system (in a containing system, which is the organisational environment). The former mode of thinking (assembly of individual parts) is reductionist or analytical, but the latter requires synthesis (Ackoff, 1999).

A principle tied closely to synthesis, and one that is essential for usability by human decision makers is the ability to 'explain' pathways of value creation – one which presupposes an understanding of the causal structure (Meredith et al., 1989) and serves as an additional mandate for the chosen model paradigm.

However, an obvious challenge for a holistic model is to retain real-world relevance – in other words, tackle the principle of incompatibility that holds that complexity makes relevance and precision impossible to obtain simultaneously (Zadeh, 1973).

Although the problem of complexity seems intractable, principles of systems thinking can provide guidance here as well – the relevant principle pertains to the architecture of complexity in systems. A systems-theoretic view holds that natural systems as well as systems of 'human ingenuity' deal with complexity by organising themselves into hierarchies. Therefore, a hierarchical organisation helps model the system by focusing on the laws of interaction more than the details of the sub-systems [Simon, (1996), pp.184–185].

An evaluation of several candidate-approaches,[4] applying the filter of 'holistic' and the related causal representation, led to system dynamics emerging as the preferred choice.

System dynamics, a field created in the 1950s by Jay Forrester to help "learn about the structure and dynamics of the complex systems" (Sterman, 2002), draws on systems thinking principles. It provides a modelling framework that enables moving away from event-driven, linear thinking of 'who did what to whom' towards providing a fuller account of consequences of actions, both intended and unintended, to explain real-world behaviour [Sterman, (2000), p.10]. It is well suited for large-scale models allied with the systems-theoretic notion that enables balancing relevance and complexity. Furthermore,

given Forrester's vision for the tool and its extensive use in the area of learning and policymaking, simulation of outcomes has always been an integral element, which satisfies the *quantitative* prerequisite as well.

A remaining challenge is one about *blended rationality*. System dynamics models predominantly use the bounded rationality frame, and support heuristic approaches but were not designed with the emerging field of big data in mind.

However, a relatively recent development allows incorporating big data analytics and AI/ML methods in system dynamics to model collaborative decision-making. It is a tool called PySD that facilitates "the integration of system dynamics models and data science" (Houghton and Siegel, 2015), thereby removing the barrier that had previously prevented combining AI/ML methods and heuristics.

In sum, the proposed approach combines system theoretic principles (for a causal representation of the problem domain), and AI/ML methods enable studying the firm performance impact of data-driven decisions.

4 Feasibility test of the proposed model using a toy problem

The toy problem, presented in this section, tests the feasibility of the proposed model in the context of a simplified manufacturing supply chain. The supply chain process configuration draws on several exemplary system dynamics (causal) models from Morecroft (1982, 1983, 1985) and Sterman (2000).

A key objective of the feasibility test is to verify the critical design choices. Therefore, the toy problem focuses on three of the most salient features of the model that have a correspondence with the three prerequisites discussed in the previous section. They are:

a can represent coordination of decisions across processes (e.g., between market forecasting and order fulfilment) (*holistic*)

b can combine heuristic procedures and AI/ML methods (*blended rationality*)

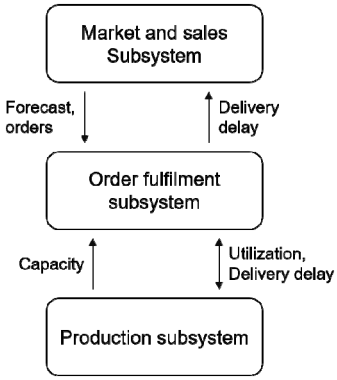
c can measure the differential impact of the use of data on performance (*quantitative*).

The implementation of 'a' takes the form of decentralised decisions based on locally available information. The results, after integration with other processes, collectively lead to outcomes that determine performance. The toy problem elicits the importance of holistic modelling by showing the impact of the lack of adequate analysis of local information processing in terms of system-wide consequences, both intended and unintended. In the case of 'b', the toy problem demonstrates a practical realisation of blended rationality in which both human judgment (modelled as heuristic procedures) and algorithmic decision-making (modelled using a causal inference ML algorithm) play a role. Finally, with regards to 'c' the toy problem elucidates the inherently quantitative nature of the modelling approach as choices such as data sources, and decision approaches lend themselves to ready analysis in terms of their impact on local as well as system-wide performance metrics.

4.1 Problem context

The structure of the exemplary supply chain is shown in Figure 1. It consists of three sub-systems: market and sales, order fulfilment, and production.

Figure 1 Structure of the exemplary supply chain



Source: Adapted from Morecroft (1983) and Sterman (2000, p.606)

The market and sales sub-system sets expectations for demand from the market. The order fulfilment sub-system satisfies demand and in the process generates capacity requirements on the production sub-system. The capacity availability and utilisation of the production sub-system result in a certain delivery delay, which then feeds back to the market that might react, for example, by depressing demands ('reneging' behaviour) if they fall below service level expectations.

4.2 Partial model test in the market and sales sub-system to verify local rationality

The market and sales sub-system perform the primary function of perceiving market demands and generating forecast orders for order fulfilment to satisfy. The behaviour is modelled essentially as an 'anchor and adjust' heuristic (the estimate is *anchored* on a quantity and is *adjusted* as new information becomes available). In this heuristic, current perceptions of demand are gradually adapted, subject to delays, based on observed inputs – a typical formulation (Morecroft, 1985) that accounts for the bounded rationality of decision makers.

A numerical example presented below explains the mechanics of the formulation. The example uses a simple system dynamics model (shown in Figure 2) that contains the structural building blocks necessary to mimic first-order exponential smoothing and serves as the template for the forecasting process in the market and sales sub-system of the toy problem.

In the example, the perceived value is set to 200 ('anchor') and is gradually adjusted to be equal to the actual input of 100 ('adjustment' to the goal value). When simulated, the slope of the perceived value is shown to be determined by the time to recognise (and adapt), which is a function of perception delays and mechanisms for deliberations of decisions (see Figure 3 and Figure 4).

Figure 2 An example of basic feedback structure and behaviour for mimicking first-order exponential smoothing

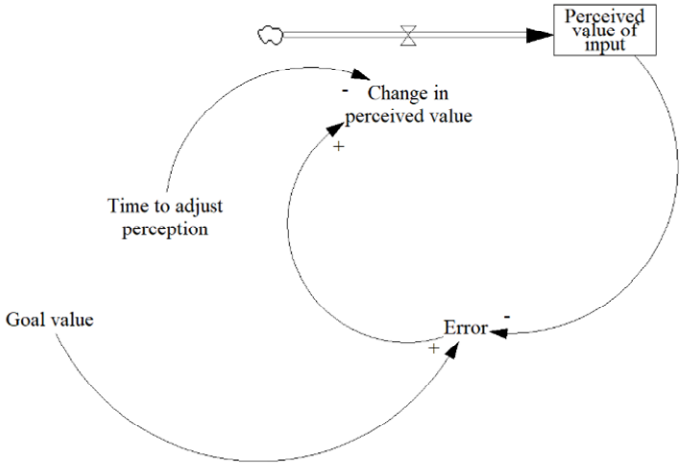


Figure 3 Market and sales sub-system – the slope of perceived value at different time lags (see online version for colours)

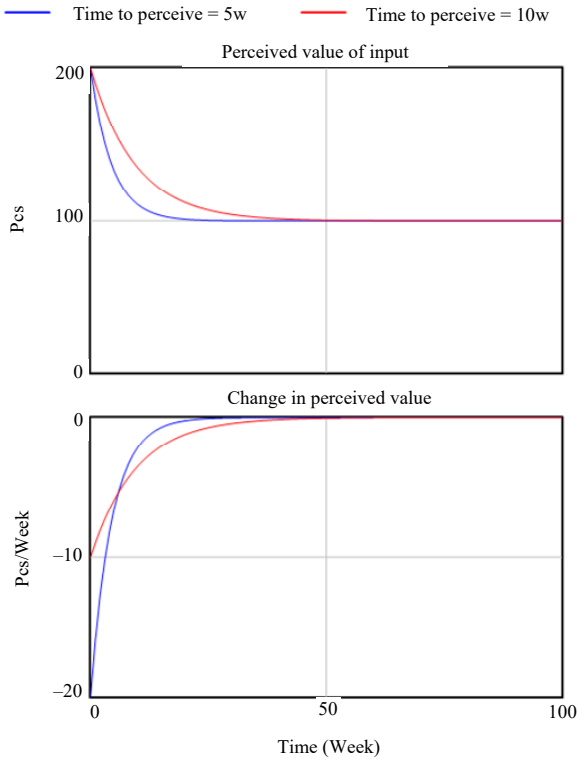
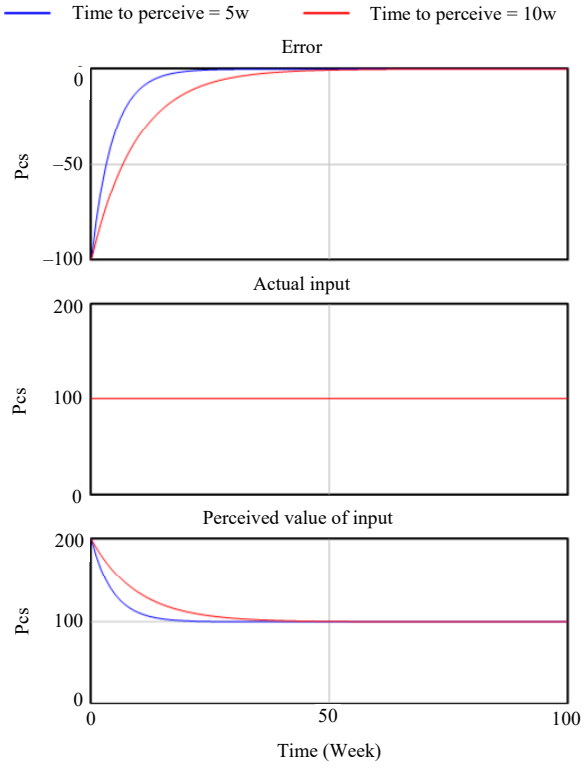


Figure 4 Market and sales sub-system – the error slope at different time lags (see online version for colours)



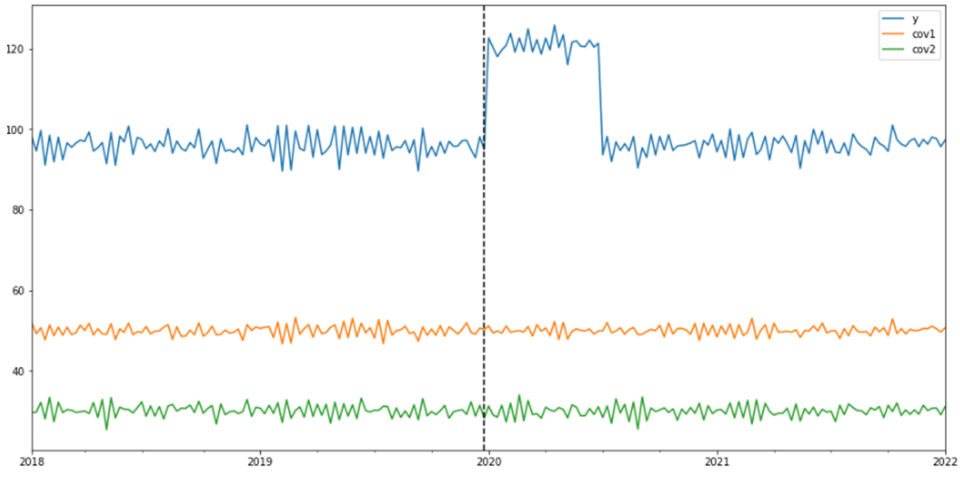
As can be seen in the graphs, the slope is steeper when the time delay is shorter (five weeks as compared to ten weeks) as the fractional rate of change is an inverse of the time to adjust perception. This construct is a first-order negative feedback loop – first-order as there is only one state variable, the perceived value of an input, involved. First-order exponential smoothing, despite its simplicity, is one of the most frequently used forecasting methods (Hogarth and Makridakis, 1981).

The forecasting mechanism implemented in the market and sales sub-system involves *enrichment* of the estimated demand, which is the output of the anchor-and-adjust heuristic, with adjustments that are based on a more sophisticated model to draw causal inference (exemplifying the blending of heuristics and machine learning). For this purpose, a causal inference model developed by Brodersen et al. (2015) is used.

The model predicts the impact of an intervention (or treatment, e.g., a marketing initiative) on the chosen response metric (or treated, e.g., promotional uplift) by regressing the time series of the response metric before the intervention on covariates that are not exposed to the same intervention. It subsequently generates a counterfactual response for the post-intervention period that is based on the 'untreated' covariates. The impact of the intervention is then the difference between the observed values and the predicted, counterfactual values.

The above idea is applied in the experiment for predicting the promotional uplift of a given market by 'training' the product demand on covariates (market demands in similar markets). The covariates are predictive of the target market but are not exposed to the same treatment (the promotional campaign).

Figure 5 Synthetic time series for target market demand (y) and covariates (cov1 and cov2) that are not impacted by the intervention (see online version for colours)



The synthetic data that is supplied to the model is shown in Figure 5. A dotted vertical line demarcates the pre and post-intervention periods. The response metric (y) is the product demand that has been shifted up due to a promotional activity that starts in the first week of 2020 and lasts around 27 weeks. However, predictors of y, namely cov1 and cov2, are not influenced by this promotional intervention and are therefore utilised to predict the counterfactual market demand in the target market 'had' the promotion not taken place. The difference yields the predicted promotional demand (indicative of the promotional effectiveness) and this demand supplements the normal demand that is estimated by the heuristic procedure.

The result of the model run (a Python version of the model was used for this purpose[5]) based on the synthetic data described is shown in Figure 6. The point effects chart shows the difference between the observed values and counterfactual predictions, which represents the point predictions for the promotional uplift.

The predictions are incorporated into the system dynamics model (shown in Figure 7) by invoking the causal inference model during the simulation run. The variable 'predicted uplift' is replaced by a PySD function that invokes the causal inference model, and the resulting promotional demand-prediction is added to the heuristic normal-demand (stock variable 'perception of market demand'). The sum of the two values constitutes the final demand (variable 'sensed demand').

Figure 6 Results of running the causal inference model on the synthetic data (see online version for colours)

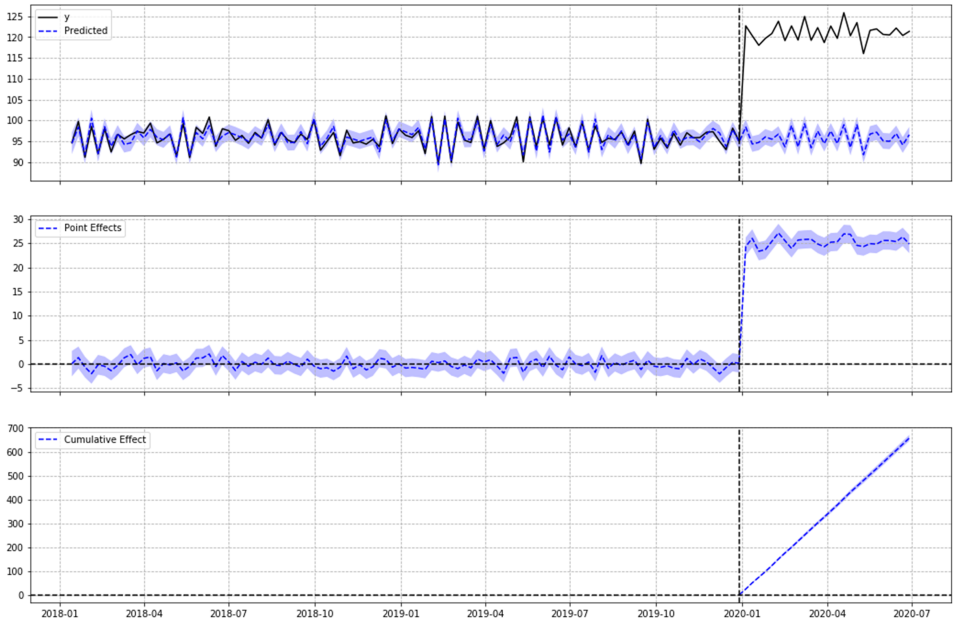
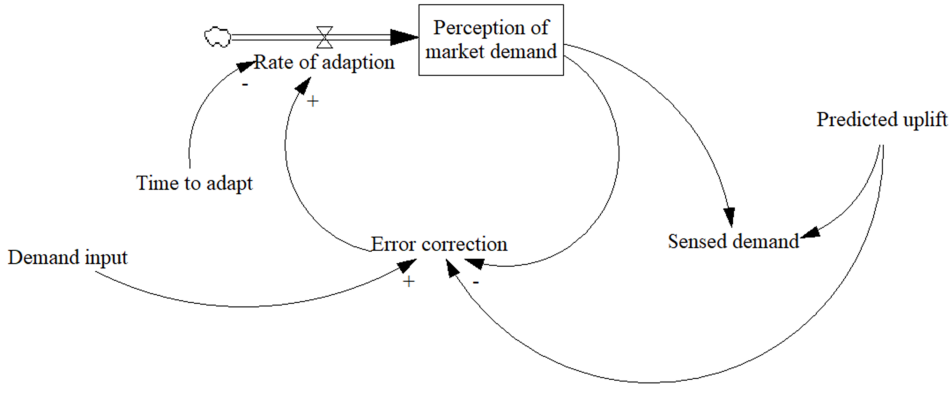


Figure 7 Structure of the forecasting sub-system



The result of the simulation run is shown in Figure 8. A comparison of forecast accuracy (using the metric mean absolute percentage error or MAPE) shows that using the causal inference model results in performance that is three percentage points better than the simple heuristic approach (see Figure 9). It makes choosing a combination of heuristic and the causal inference model a 'locally rational decision'.

Figure 8 Results of the simulation run incorporating promotional uplift predicted by the causal inference model (see online version for colours)

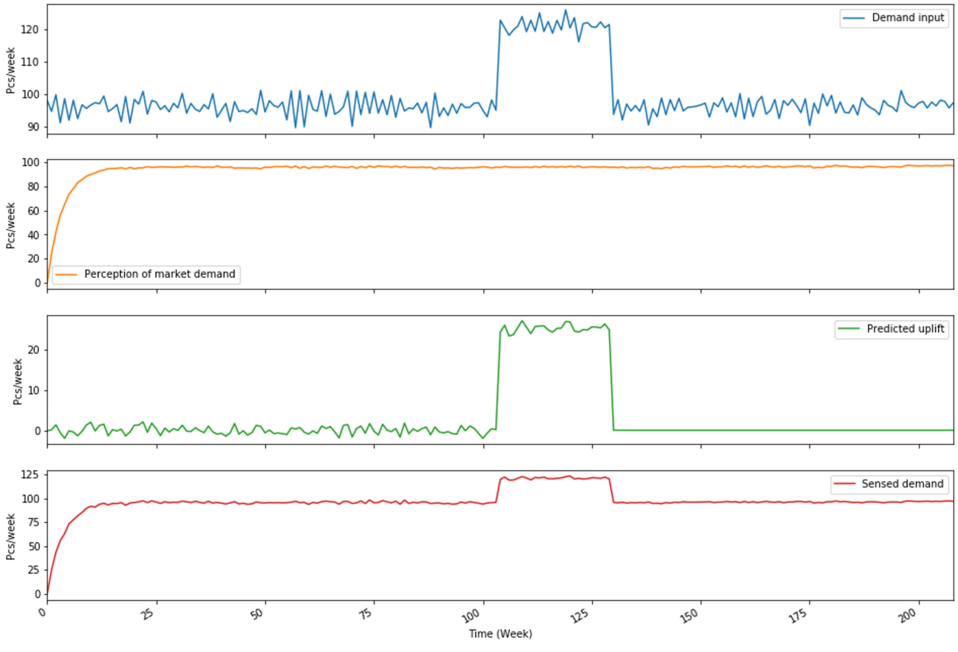
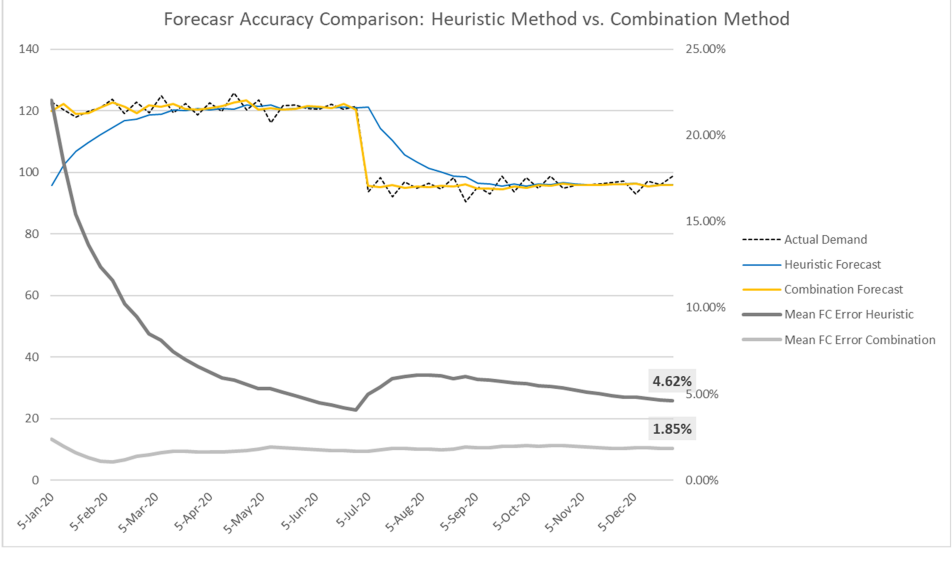


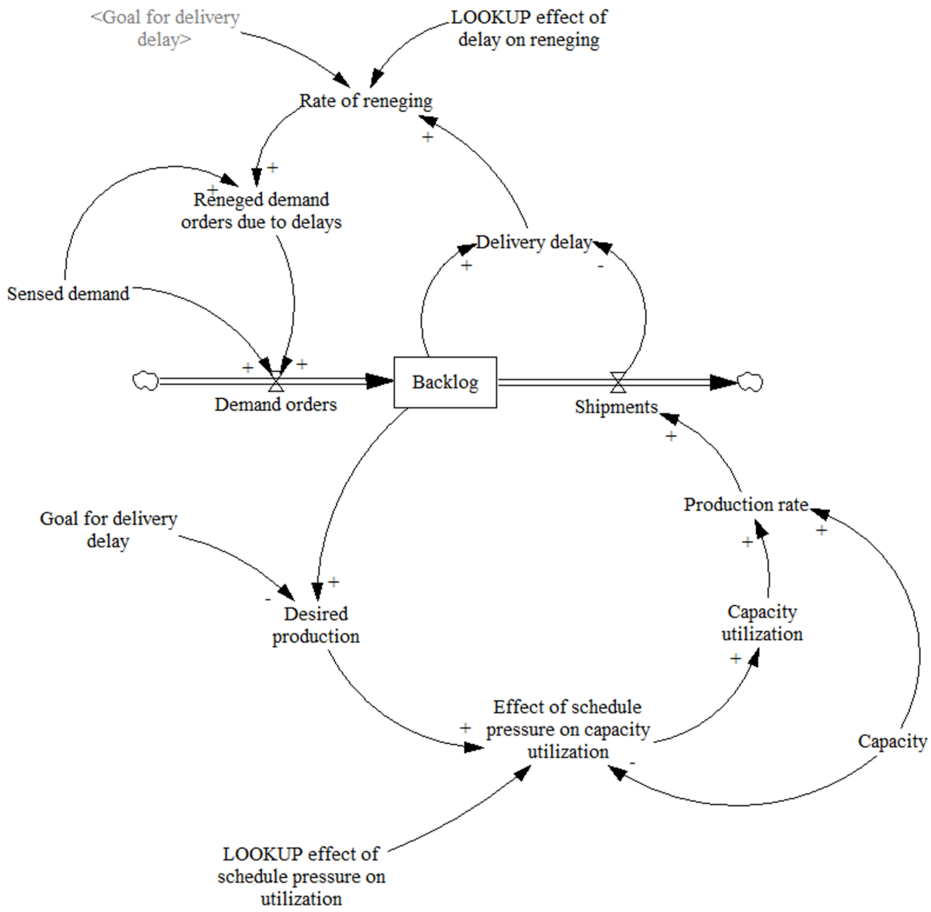
Figure 9 Comparison of forecast accuracy between a pure heuristic approach and an approach that combines heuristic and causal inference (see online version for colours)



4.3 Full model test to check system-wide impact

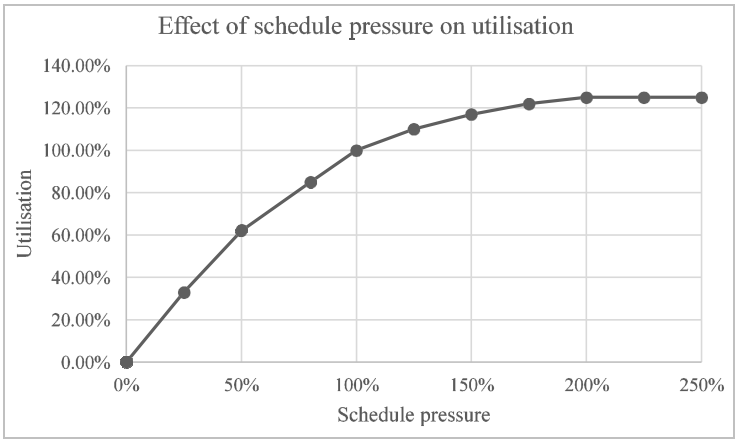
Augmenting the heuristic with the predictive capability of the causal inference model seems to have improved the performance of the marketing and sales sub-system. However, by including the production and order fulfilment sub-systems (see Figure 10), the performance appears to deteriorate. The reason is that the increase in demand conflicts with available capacity and flexibility factors (ability to go beyond the 'theoretical maximum' capacity utilisation owing to demand-side pressures).

Figure 10 Structure of the system after including the production and order fulfilment sub-systems



The adjustment of capacity utilisation is made in response to the mounting schedule pressure, which is a function of the ratio between the actual delivery delay and the goal for the delivery delay. Capacity utilisation is modelled as a function of schedule pressure, which in turn is the ratio between desired production and available capacity. When the production desired is equal to available capacity, the schedule pressure equals one, and consequently, the utilisation is at 100%. Beyond 100%, utilisation tapers off and saturates at the maximum value of 125% (see Figure 11).

Figure 11 Nonlinear relationship between schedule pressure and capacity utilisation



However, the resulting increase in capacity utilisation is insufficient to keep the delivery delay down, and it results in the market reneging and, consequently, leads to lost sales. The reneging behaviour is incorporated to consider the reputational impact of increasing delays whereby customers renege and switch over to other alternatives. It is implemented by using a table function in the simulation model, where the effect of the dependent variable (loss of demand) is a function of the independent variable (delivery delays). A table function in system dynamics is like a lookup function in a spreadsheet program that allows specification of value pairs of the form 'x(n), y(n)' (where n is an index) that helps to model the nonlinear relationships whereby y(n) is the effect of x(n). The reneging effect modelled for the experiment is shown in Figure 12. As a result of reneging, market demand is depressed until parity is restored when the shipment rate can keep up with incoming orders.

Figure 12 Nonlinear relationship between delay and loss of market demand

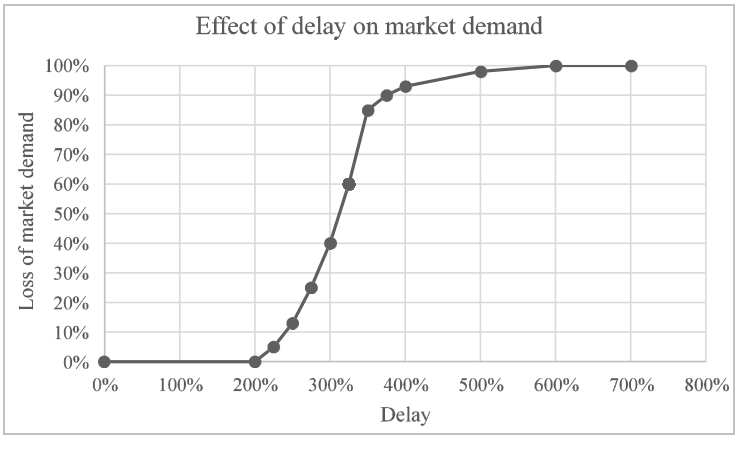
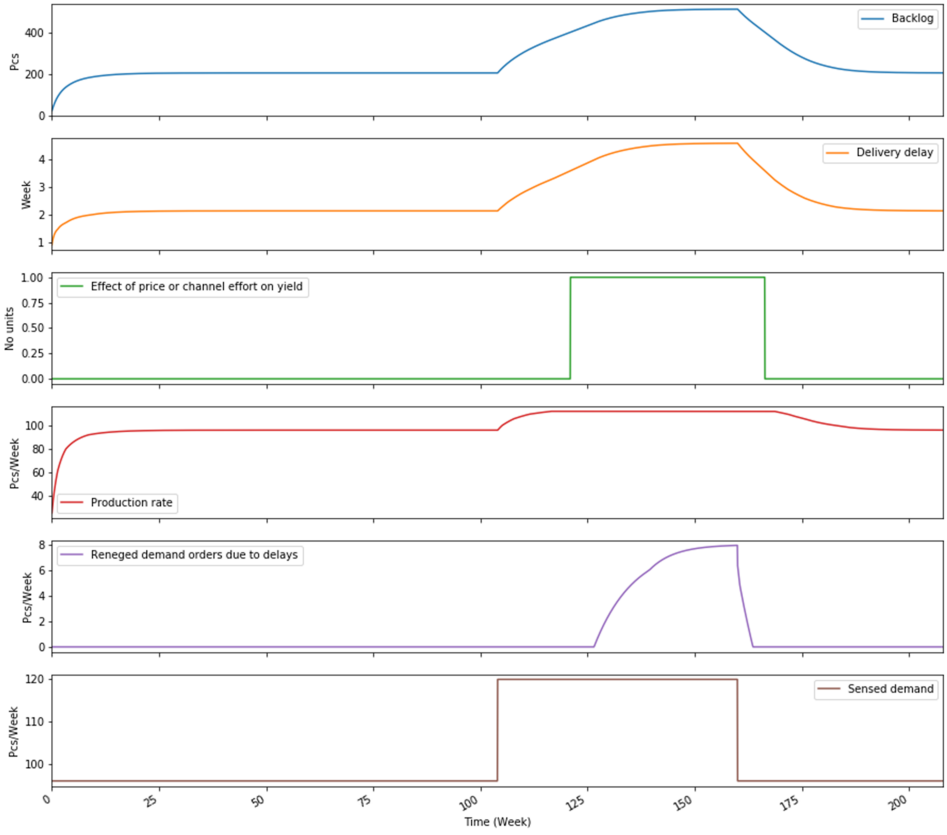


Figure 13 Simulation results showing capacity insufficiency leading to delays that in turn result in customer-reneging behaviour (lost sales) (see online version for colours)



The result of the simulation is shown in Figure 13. The increase in demand due to the promotional campaign is modelled as a step function, and the resulting increase in delivery delay leads eventually to lost orders (chart 'reneged demand orders due to delays') as the flexing of capacity utilisation is insufficient to keep the delays below the acceptable limit.

Thus, the experiment demonstrates how a locally rational decision can lead to dysfunctional behaviour and one that can only be fully captured by modelling the causal structure of the entire system.

The experiment also touches on the core trade-off that underlies the approach for the proposed measurement model. It is one between decentralised decision-making supported by AI/ML approaches fed with big data incurring low coordination effort (coordinating decisions across decision-making hierarchies), and boundedly rational decision-making that employs various rules of thumb and heuristics, but involves a higher number of exceptions that need to be coordinated (also implying higher latency or time delays).

The experiment also demonstrates the viability of the novel approach to combine the system dynamics modelling framework (simulated in the VenSim tool) with the PySD toolkit providing advanced analytical tools, for meeting the requirements for an effective quantitative model outlined in Section 3.

5 Summary and conclusions

Recent years have seen increased investments in digital technologies that have created an environment of abundant data or big data and facilitate a multitude of opportunities for data-driven decisions (e.g., Brynjolfsson et al., 2011; Porter and Heppelmann, 2015). Concurrently, organisations are struggling to fully capitalise on big data as there is an underinvestment in the understanding of it (e.g., IDC, 2014; LaValle et al., 2011; Ross et al., 2013; Shah et al., 2012).

There is theoretical and empirical support, and case evidence that suggests any understanding of the pathways of value creation of big data can only happen when placed in the context of organisational-complementarities that give an accurate account of synergistic effects (e.g., Brynjolfsson and Milgrom, 2012; Ross et al., 2017; Wernerfelt, 1984). However, organisations lack the means to evaluate big data to understand its impact in terms of 'insightfulness and risks' (Abbasi et al., 2016).

This paper proposed a design for a quantitative model that combines system-theoretic principles embodied in system dynamics, and data science and AI/ML methods that allow the exploration of big data's impact on value through simulation. The system dynamics approach enables representing the causal structure of the problem, which in turn helps 'treat' data as an intervention to study its impact on chosen performance metrics. Although prior research exists on system dynamics models that allow answering questions about the value of information, the ability to incorporate AI/ML methods to then truly study performance impact of characteristics unique to big data is a novel one.

This paper also included a description of a feasibility test using a toy problem conducted on a small-scale prototype of the proposed design. The feasibility test, set in a supply chain context, demonstrated the viability of some of the core design principles. Firstly, a causal structure to capture complementarities (e.g., modelled as interactions between multiple functional processes). Secondly, the ability to use a combination of AI/ML methods (e.g., a causal inference ML method) and heuristics (e.g., anchor-and-adjust heuristic). Finally, the ability to quantify the performance impact of data (e.g., forecast accuracy using mean absolute percentage error or MAPE).

This paper contributes to the value of information literature by answering the call for contributions (Abbasi et al., 2016) that explore the interplay between big data characteristics and the decision-making process of an organisation. Specifically, the proposed modelling paradigm addresses questions about role delineation between algorithms and intuition, a question with real-world significance (e.g., Barro and Davenport, 2019; Saenz et al., 2020).

The implications for decision makers are that models developed on the proposed design can help explore the consequences of different configurations of decision-making (e.g., decentralised/centralised, a different mix of machine and human rationality) in a simulation setting to make informed investment decisions.

The model proposed, and the feasibility test is but the first step towards developing a fully-fledged quantitative-measurement model. The logical next step might be to use the recommended approach to develop a conceptual-model-template for a chosen problem domain (e.g., closed-loop supply chain), and further to adapt the conceptual decision-making schema to a particular organisation for use by practitioners.

References

Abbasi, A., Sarker, S. and Chiang, R. (2016) 'Big data research in information systems: toward an inclusive research agenda', *Journal of the Association for Information Systems*, Vol. 17, No. 2, pp.i–xxxii.

Ackoff, R.L. (1999) *Re-creating the Corporation: A Design of Organizations for the 21st Century*, Ackoff, R.L. (Ed.): Oxford University Press, New York, Oxford.

Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R. and Childe, S.J. (2016) 'How to improve firm performance using big data analytics capability and business strategy alignment?', *International Journal of Production Economics*, Vol. 182, pp.113–131.

Anderson, C. (2008) *The End of Theory: The Data Deluge Makes the Scientific Method Obsolete*, Wired [online] https://www.wired.com/2008/06/pb-theory/ (accessed 23 April 2020).

Barro, S. and Davenport, T.H. (2019) 'People and machines: partners in innovation', *MIT Sloan Management Review*, Vol. 60, No. 4 pp.22–28.

Bertrand, J. and Fransoo, J. (2002) 'Operations management research methodologies using quantitative modelling', *International Journal of Operations & Production Management*, Vol. 22, No. 2, pp.241–264.

Bielinska-Kwapisz, A. (2003) 'Sufficiency in Blackwell's theorem', *Mathematical Social Sciences*, Vol. 46, No. 1, pp.21–25.

Brodersen, K.H., Gallusser, F., Koehler, J., Remy, N. and Scott, S.L. (2015) 'Inferring causal impact using Bayesian structural time-series models', *The Annals of Applied Statistics*, Vol. 9, No. 1, pp.247–274.

Brynjolfsson, E. and Hitt, L.M. (2000) 'Beyond computation: information technology, organizational transformation and business performance', *Journal of Economic Perspectives*, Vol. 14, No. 4, pp.23–48.

Brynjolfsson, E. and McAfee, A. (2016) 'Where computers defeat humans, and where they can't', *New York Times* [online] https://www.nytimes.com/2016/03/16/opinion/where-computers-defeat-humans-and-where-they-cant.htm1 (accessed 23 April 2020).

Brynjolfsson, E. and McAfee, A. (2017) 'The business of artificial intelligence', *Harvard Business Review* [online] https://hbr.org/cover-story/2017/07/the-business-of-artificial-intelligence (accessed 23 April 2020).

Brynjolfsson, E. and Milgrom, P. (2012) 'Complementarity in organizations', in Gibbons, R. and Roberts, J. (Eds.): *The Handbook of Organizational Economics*, pp.11–55, Princeton University Press, Princeton.

Brynjolfsson, E. and Mitchell, T. (2017) 'What can machine learning do? Workforce implications', *Science*, Vol. 358, No. 6370, pp.1530–1534.

Brynjolfsson, E., Hitt, L.M. and Kim, H.H. (2011) 'Strength in numbers: how does data-driven decision-making affect firm performance?', *SSRN Electronic Journal* [online] https://ssrn.com/abstract=1819486 (accessed 23 April 2020).

Carr, N. (2003) 'IT doesn't matter', *Harvard Business Review* [online] https://hbr.org/2003/05/it-doesnt-matter (accessed 26 April 2020).

Davenport, T.H. (2006) *Competing on Analytics* [online] https://hbr.org/2006/01/competing-on-analytics (accessed 25 April 2020).

Davenport, T.H., Barth, P. and Bean, R. (2012) 'How 'big data' is different', *MIT Sloan Management Review*, Fall, Vol. 54, No. 1, pp.22–24.

Dolgui, A., Ivanov, D. and Rozhkov, M. (2020) 'Does the ripple effect influence the bullwhip effect? An integrated analysis of structural and operational dynamics in the supply chain', *International Journal of Production Research*, Vol. 58, No. 5, pp.1285–1301.

Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2019) 'Artificial intelligence for decision making in the era of big data – evolution, challenges and research agenda', *International Journal of Information Management*, Vol. 48, pp.63–71.

Fox, J. (2015) 'From 'economic man' to behavioral economics', *Harvard Business Review* [online] https://hbr.org/2015/05/from-economic-man-to-behavioral-economics (accessed 1 April 2020).

Frank, M.R., Autor, D., Bessen, J.E., Brynjolfsson, E., Cebrian, M., Deming, D.J., Feldman, M., Groh, M., Lobo, J., Moro, E., Wang, D., Youn, H. and Rahwan, I. (2019) 'Toward understanding the impact of artificial intelligence on labor', *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 116, No. 14, pp.6531–6539.

Galbraith, J.R. (2014) 'Organizational design challenges resulting from big data', *Journal of Organization Design*, Vol. 3, No. 1, p.2.

Gigerenzer, G. and Goldstein, D.G. (2011) 'Reasoning the fast and frugal way: models of bounded rationality', in Gigerenzer, G., Hertwig, R. and Pachur, T. (Eds.): *Heuristics*, pp.33–55, Oxford University Press, New York.

Glazer, R., Steckel, J.H. and Winer, R.S. (1992) 'locally rational decision making: the distracting effect of information on managerial performance', *Management Science*, Vol. 38, No. 2, pp.212–226.

Grimmer, J. (2015) 'We are all social scientists now: how big data, machine learning, and causal inference work together', *PS: Political Science & Politics*, Vol. 48, No. 1, pp.80–83.

Harford, T. (2014) 'Big data: a big mistake?', *Significance*, Vol. 11, No. 5, pp.14–19.

Helbing, D. (2013) 'Globally networked risks and how to respond', *Nature*, Vol. 497, No. 7447, pp.51–59.

Hofmann, P. and Reiner, G. (2006) 'Drivers for improving supply chain performance: an empirical study', *Int. J. Integrated Supply Management*, Vol. 2, No. 3, pp.214–230.

Hogarth, R.M. and Makridakis, S. (1981) 'Forecasting and planning: an evaluation', *Management Science*, Vol. 27, No. 2, pp.115–138.

Houghton, J. and Siegel, M. (2015) 'Advanced data analytics for system dynamics models using PySD', *Proceedings of the 33rd International Conference of the System Dynamics Society*.

Howard, R. (1966) 'Information value theory', *IEEE Transactions on Systems Science and Cybernetics*, Vol. 2, No. 1, pp.22–26.

IDC (2014) *The Digital Universe of Opportunities: Rich Data and the Increasing Value of the Internet of Things* [online] https://www.emc.com/leadership/digital-universe/2014iview/high-value-data.htm (accessed 1 April 2020).

Ivanov, D. and Dolgui, A. (2020) 'Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak', *International Journal of Production Research*, Vol. 58, No. 10, pp.2904–2915.

Ivanov, D., Dolgui, A. and Sokolov, B. (2019) 'The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics', *International Journal of Production Research*, Vol. 57, No. 3, pp.829–846.

Jordan, M.I. and Mitchell, T.M. (2015) 'Machine learning: trends, perspectives, and prospects', *Science*, Vol. 349, No. 6245, pp.255–260.

Kahneman, D. (2011) *Thinking, Fast and Slow*, Farrar, New York.

Kavadias, S., Ladas, K. and Loch, C. (2016) *The Transformative Business Model* [online] https://hbr.org/2016/10/the-transformative-business-model (accessed 1 April 2020).

LaValle, S., Lesser, E., Shockley, R., Hopkins, M.S. and Kruschwitz, N. (2011) *Big Data, Analytics and the Path from Insights to Value* [online] https://sloanreview.mit.edu/article/big-data-analytics-and-the-path-from-insights-to-value/ (accessed 1 April 2020).

Lindebaum, D., Vesa, M. and den Hond, F. (2020) 'Insights from 'the machine stops' to better understand rational assumptions in algorithmic decision making and its implications for organizations', *Academy of Management Review*, Vol. 45, No. 1, pp.247–263.

Lyneis, J.M. (2000) 'System dynamics for market forecasting and structural analysis', *System Dynamics Review*, Vol. 16, No. 1, pp.3–25.

March, J.G. (1978) 'Bounded rationality, ambiguity, and the engineering of choice', *The Bell Journal of Economics*, Vol. 9, No. 2, p.587.

March, J.G. and Simon, H.A. (1993) 'Organizations revisited', *Industrial and Corporate Change*, Vol. 2, No. 3, pp.299–316.

McAfee, A. and Brynjolfsson, E. (2008) 'Investing in the IT that makes a competitive difference', *Harvard Business Review* [online] https://hbr.org/2008/07/investing-in-the-it-that-makes-a-competitive-difference (accessed 25 April 2020).

McAfee, A. and Brynjolfsson, E. (2012) 'Big data: the management revolution', *Harvard Business Review* [online] https://hbr.org/2012/10/big-data-the-management-revolution (accessed 28 April 2020).

McAfee, A. and Brynjolfsson, E. (2017) *Machine, Platform, Crowd: Harnessing our Digital Future*, 1st ed., W.W. Norton & Company, New York.

Melville, N., Gurbaxani, V. and Kraemer, K. (2004) 'Review: information technology and organizational performance: an integrative model of IT business value', *MIS Quarterly*, Vol. 28, No. 2, p.283.

Mendelson, H. and Pillai, R. (1999) 'Information age organizations, dynamics and performance', *Journal of Economic Behavior & Organization*, Vol. 38, No. 3, pp.253–281.

Meredith, J.R., Raturi, A., Amoako-Gyampah, K. and Kaplan, B. (1989) 'Alternative research paradigms in operations', *Journal of Operations Management*, Vol. 8, No. 4, pp.297–326.

Mithas, S., Ramasubbu, N. and Sambamurthy, V. (2011) 'How information management capability influences firm performance', *MIS Quarterly*, Vol. 35, No. 1, p.237.

Morecroft, J. (1982) 'A critical review of diagraming tools for conceptualizing feedback system models', *Dynamica*, Vol. 8, No. 1, pp.20–29.

Morecroft, J. (1983) 'System dynamics: portraying bounded rationality', *Omega*, Vol. 11, No. 2, pp.131–142.

Morecroft, J. (1985) 'Rationality in the analysis of behavioral simulation models', *Management Science*, Vol. 31, No. 7, pp.900–916.

Pearl, J. and Mackenzie, D. (2018) *The Book of Why: The New Science of Cause and Effect*, 1st ed., Basic Books, New York.

Pomerol, J-C. (1997) 'Artificial intelligence and human decision making', *European Journal of Operational Research*, Vol. 99, No. 1, pp.3–25.

Porter, M.E. and Heppelmann, J.E. (2014) *How Smart, Connected Products Are Transforming Competition* [online] https://hbr.org/2014/11/how-smart-connected-products-are-transforming-competition (accessed 25 April 2020).

Porter, M.E. and Heppelmann, J.E. (2015) *How Smart, Connected Products Are Transforming Companies* [online] https://hbr.org/2015/10/how-smart-connected-products-are-transforming-companies (accessed 25 April 2020).

Provost, F. and Fawcett, T. (2013) 'Data science and its relationship to big data and data-driven decision making', *Big Data*, Vol. 1, No. 1, pp.51–59.

Ross, J. (2017) *Don't Confuse Digital with Digitization* [online] https://sloanreview.mit.edu/article/dont-confuse-digital-with-digitization/ (accessed 25 April 2020).

Ross, J., Beath, C. and Quaadgras, A. (2013) 'You may not need big data after all', *Harvard Business Review* [online] https://hbr.org/2013/12/you-may-not-need-big-data-after-all (accessed 1 April 2020).

Ross, J., Sebastian, I., Beath, C. and Jha, L. (2017) *Designing Digital Organizations – Summary of Survey Findings* [online] https://media-publications.bcg.com/MIT-CISR-Designing-Digital-Survey.PDF (accessed 1 April 2020).

Russell, S.J. (2019) 'Human compatible: artificial intelligence and the problem of control', *Viking*, New York.

Saenz, M.J., Revilla, E. and Simón, C. (2020) *Designing AI Systems with Human-Machine Teams* [online] https://sloanreview.mit.edu/article/designing-ai-systems-with-human-machine-teams/ (accessed 5 April 2020).

Scheibe, K.P. and Blackhurst, J. (2018) 'Supply chain disruption propagation: a systemic risk and normal accident theory perspective', *International Journal of Production Research*, Vol. 56, Nos. 1–2, pp.43–59.

Schölkopf, B. (2019) *Causality for Machine Learning* [online] http://arxiv.org/pdf/1911.10500v2 (accessed 5 April 2020).

Shah, S., Horne, A. and Capellá, J. (2012) 'Good data won't guarantee good decisions', *Harvard Business Review* [online] https://hbr.org/2012/04/good-data-wont-guarantee-good-decisions (accessed 28 April 2020).

Silver, E.A., Pyke, D.F. and Peterson, R. (1998) *Inventory Management and Production Planning and Scheduling*, 3rd ed., Wiley, New York, NY.

Simon, H.A. (1996) *The Sciences of the Artificial*, 3rd ed., MIT Press, Cambridge, Mass., London.

Simon, H.A. (1997) *Administrative Behavior: A Study of Decision-making Processes in Administrative Organizations*, Simon, H.A. (Ed.): 4th ed., Free Press, New York, London.

Sterman, J. (2000) *Business Dynamics: Systems Thinking and Modeling for a Complex World*, Irwin/McGraw-Hill, Boston.

Sterman, J. (2002) 'System dynamics: systems thinking and modeling for a complex world', *ESD International Symposium*.

Tabrizi, B., Lam, E., Gerard, K. and Irvin, V. (2019) 'Digital transformation is not about technology', *Harvard Business Review* [online] https://hbr.org/2019/03/digital-transformation-is-not-about-technology (accessed 25 April 2020).

Tambe, P., Hitt, L.M. and Brynjolfsson, E. (2012) 'The extroverted firm: how external information practices affect innovation and productivity', *Management Science*, Vol. 58, No. 5, pp.843–859.

Vlachos, D., Georgiadis, P. and Iakovou, E. (2007) 'A system dynamics model for dynamic capacity planning of remanufacturing in closed-loop supply chains', *Computers & Operations Research*, Vol. 34, No. 2, pp.367–394.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J-f., Dubey, R. and Childe, S.J. (2017) 'Big data analytics and firm performance: effects of dynamic capabilities', *Journal of Business Research*, Vol. 70, pp.356–365.

Weill, P. and Woerner, S.L. (2018) 'Is your company ready for a digital future?', *MIT Sloan Management Review*, Vol. 59, No. 2, pp.21–25.

Wernerfelt, B. (1984) 'A resource-based view of the firm', *Strategic Management Journal*, Vol. 5, No. 2, pp.171–180.

Westerman, G., Bonnet, D. and McAfee, A. (2014) 'Leading digital: turning technology into business transformation', *Harvard Business Review Press*, Boston, Massachusetts.

Woehner, H., Darkow, I-L. and Kaiser, G. (2013) 'How do information technology and integrative planning drive performance in today's supply chains?', *Int. J. Integrated Supply Management*, Vol. 8, Nos. 1/2/3, pp.5–23.

World Economic Forum (2019) *How Much Data is Generated Each Day?* [online] https://www.weforum.org/agenda/2019/04/how-much-data-is-generated-each-day-cf4bddf29f/ (accessed 25 April 2020).

Zadeh, L. (1973) 'Outline of a new approach to the analysis of complex systems and decision processes', *IEEE Trans. SMC, SMC-3*, January, Vol. SMC-3, No. 1, pp.28–44.

Notes

1 Zettabyte = $1{,}000^7$ bytes.

2 After computer, and the internet.

3 Examples include: AlphaGo winning against a human world champion at Go, IBM Watson winning at Jeopardy! Against a human player, Watson's success with generating scientific hypotheses, Google DeepMind's ML improving cooling efficiency, after having been optimised by human experts, by more than 15% (source: Brynjolfsson and McAfee, 2016, 2017).

4 The other approaches considered were: OR, optimisation methods, AI/ML methods, and approximate dynamic programming.

5 'Pycausalimpact' is a Python version of the CausalImpact model originally developed for R by Brodersen et al. (2015). The Python version allows for incorporating the model into the PySD setup that combines system dynamics with big data and machine learning algorithms.