Developing a Smart Operational Research with Hybrid Practice Theories

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Abstract – The growth of technology-rich data-driven decision environments is seen by some as a challenge to the future relevance of Operational Research. Extant research remains unspecific about the distinct contribution that Operational Research can make in environments that are influenced by big data, data science and analytics. This paper explores the possibility that these environments hold the potential for a new integrative Operational Research offering, which we conceptualise as Smart Operational Research. In developing this proposal, we combine automated co-occurrence analysis of a corpus of literature with human-driven data interpretation to identify instantiations of hybrid decision-making. We then bring theory and practice together to outline the Smart Operational Research framework with the overall aim to enhance actionable insight and positive results for Operational Research practitioners.

Keywords – Decision processes; Hybrid practice theories; Decision-support; Hybridity; Co-occurrence mapping

1 INTRODUCTION

Data-driven decision-making, made possible by advances in big data, data science, and data analytics is increasingly being seen as an essential capability for the development of a strategic advantage at the organisational level (Agarwal & Dhar, 2014; Davenport & Harris, 2007). Coupled with the transformational development of information and communication technologies, the tools and activities associated with data-driven decision-making are engendering new ways of working on a range of organisational problems (Davenport & Harris, 2007; Davenport et al., 2010; Sharma et al., 2014). However, the question of how best to make sense of big data, data analytics and data science and identify how they might be best used to make sense of organisational realities remains to be answered (Kitchin & McArdle, 2016). In attempting to answer this question, we need to consider whether data-driven decision-making is distinct from traditional Operational Research (OR), which originated as a discipline in a time when access to digital data was limited (Kitchin, 2014a, 2014b). Therefore, this paper aims to address the question: how can emerging technology-rich data-driven decision environments contribute to the practice of OR, or vice versa?

Much attention is being given to the place that OR has in supporting data-driven decision-making (Doumpos & Zopounidis, 2016; Mortenson et al., 2015; Ranyard et al., 2015). For example, the aim of OR in providing decision support through modelling, optimisation, and statistics makes it seem similar to the purpose of business analytics (Hazen et al., 2016). However, while the toolsets of OR and business analytics overlap substantially, it is continuously contended that the two fields are not identical (Robinson et al., 2010). One suggestion is that many of the analytical techniques that have been applied in OR may, at times, be complemented by advanced data-mining and machine learning methods, and access to large databases and decision support systems (Tsoukias et al., 2013). However, ongoing challenges with data-driven decision-making and OR relate to the ease of use of tools and techniques by OR practitioners, and the identification of innovative ways to reduce the complexity of data analysis and the presentation of results (Hazen et al., 2016).

Of the many issues that OR practitioners could raise about the relationship between technology-rich data-driven decision support and OR, one aspect stands out and will be the main concern for this paper. While the more analytical elements from big data, analytics and data science and OR seem on the surface complementary, the more pragmatic perspectives of OR appear difficult at times to reconcile with some of the rationalisation and algorithmic techniques of these approaches (Mortenson et al., 2015). Here, much of the literature appears to propagate the unwavering belief

that ‘big data’ leads to ‘big impact’ (Chen et al., 2012; Gangadharan & Swami, 2004). However, the mechanical application of analytical tools – even highly sophisticated ones – to data, does not automatically lead to actionable insight (Sharma et al., 2014). Rather, in the case of automated decision-making, the interpretation of models is based on the rules programmed into a system, whereas in the case of human decision-makers, we still arrive at actionable insight through an active process of developing understanding. As such, while automated analytics applications may facilitate the identification of patterns, we still need to make sense of these patterns in order to transform them into actionable insights (Hilbert, 2012). One suggestion is that OR, with its origins as a practice-based discipline and its attention to real-world concerns (Royston, 2013), might in conjunction with technology-rich data-driven decision support processes help with the creation of new and actionable insights to guide organisational decision-making (Tsoukias et al., 2013). It thus seems to be the combination of data-driven decision support and context-specific (human) resources, in the form of expertise, judgment and knowledge, that allow actionable patterns to be identified for different settings and to create new opportunities for improvements in organisations. However, there is a lack of research that explores this combination in detail.

We argue, specifically, that there is a lack of a framework to help with the aforementioned issues. We propose to address this gap through the following. First, we advance theoretical developments that may support our understanding of the processes involved in generating actionable insights. We question the taken-for-granted notion that technology-rich data-driven decision environments, by virtue of tools and methods alone, can enhance opportunities for improvement in organisations. In other words, we question whether prior research on big data, data science and data analytics has not merely emphasised discontinuous, momentary and fragmented insight while failing to capture the processes by which practitioners develop actionable knowledge in social contexts. Second, we seek to identify instances of the challenges involved in developing actionable insight by way of mapping relevant literature. To do this, we begin by identifying what these contexts are made up of through a process of bibliometric analysis and in-depth qualitative data exploration. Third, we present a framework that we call SMART OR, to facilitate the development of alternative hybrid approaches that may lead to actionable insights. Specifically, we present a set of guiding questions that OR practitioners may use with their clients when seeking to develop decision-aiding practice in environments where decision-makers may see enhancements in data, data science, and analytics increasingly as essential capabilities.

2 RELATED RESEARCH AND THEORETICAL BASIS

OR has a long history of developing and delivering actionable insight through its integrative approaches (Keys, 1995, 1997). However, OR practitioners have not yet clearly articulated the role of technology-rich data-driven decision environments in enhancing organisational capability for developing actionable knowledge, even though some have recognised this challenge as highly relevant (Vidgen et al., 2017; Wamba et al., 2017). For example, Ranyard et al. (2015, p.10) argue that "*the core difference between analytics and OR is not merely in the tool set [...] but also on the organisational abilities to recognise opportunities to re-engineer core processes*". We have three concerns with the predominant thinking on technology-rich data-driven decision environments in relation to their potential relevance for OR.

First, OR has a long history in supporting strategic decisions that involve multiple stakeholders and organisations (Rosenhead & Mingers, 2001). In such contexts, negotiated action is facilitated by requisite decision models (Phillips, 1982) that represent accommodations of different partial perspectives of stakeholders (Eden, 1992; Eden & Ackermann, 2000, 2013). However, prior research in big data, analytics and data science has focussed mainly on the technology infrastructure (Liberatore & Luo, 2013), rather than the use of the technology-produced evidence in participatory group decision processes that are characteristic of many organisational decision practices today, leading to our first concern about the tension between technology use and a ubiquitous technology infrastructure. It is not the technologies *per se* that matter for organisational decision-making, but rather how their use reshapes how accommodation of different perspectives for action in an organisation is accomplished as decision-makers and their technologies are (mis)aligned in the pursuit of organisational objectives (Pels et al., 2002; Teece, 2007). There is thus a greater need to theorise the connection between humans and technology in decision practices, which considers that they are jointly – albeit to differing degrees – constitutive of decision processes in today's organisations.

Second, the importance of producing actionable knowledge (Argyris, 1996; Cross & Sproull, 2004), has become even more critical in recent years with the vast expansion of data availability and the need for quick and effective decision-making (Bumblauskas et al., 2017). Yet, the relationship between requisite and actionable knowledge (Phillips, 1984) and the role of technology-rich data-driven decision support systems in framing, influencing, legitimising and demonstrating what counts as noteworthy insight is thus far under-theorised (Tenkasi & Hay, 2008). A particular challenge is the lack of understanding of how digitally-mediated engagement qualitatively changes decision processes

(Ayanso & Visser, 2015; Pistilli et al., 2014; Sauter, 2011). As such, the effect of introducing technology-rich data-driven decision support in traditional decision-making environments is not yet clear (Lin, 2014; Loshin, 2012). Specifically, OR practitioners need to give more consideration to the complex processes of knowledge production with these technologies, which are often imbued with symbolic and political meaning and which we can therefore not adequately conceptualise as a technical production process (Cetina, 1995). Embedded in the quest for actionable knowledge through more complex technology-support is the ideal of automation or self-optimisation in closed systems. However, there appears to be limited consideration of the need for a wider collective or open concern, i.e. a realisation on distributed action by multiple stakeholders together with analytics. An important development in this regard is that, more recently, OR scholars have stressed the importance of understanding how technological platforms that connect multiple stakeholders help with the production of actionable insights (e.g. Ackermann & Eden, 2005; Hindle & Vidgen, 2017; Mingers & Rosenhead, 2004; Yearworth & White, 2016)

Third, a lack of structure, and uncertainty inherent in their future orientation and ambiguity about the relevant aspects that matter often characterises strategically important decisions. Hence, the chasm between the technical superiority of digital technology in developing models through analytics, and the ambiguity in the process of decision formation as experienced by decision-makers, persists (Liebowitz, 2013). As such, the interaction of human decision-makers with data and analytics is unlikely to resemble a rational process (Simon, 1971) as newly available data and models challenge long-standing practices and beliefs (Liebowitz, 2013). This suggests that we still do not understand how to enable the development of *actionable insight*, where the experience of decision-makers, whose time and attention is a scarce resource (Simon, 1971), is integrated with data-driven decision-making in ways that help to develop balanced judgements (Liebowitz, 2013) and/or *sounder* decisions. More abstractly, the challenge here is to understand how to effectively reconcile the relationship between subjective, internalised knowing and the objective (lack of) external(ised) knowledge (White, 2016). As such, the question is how to trace and develop the possible connections between technologies that promise certainty through ever more big data and the self-affirming actionable and experience-based insight of practitioners whose origins may not be clearly articulable.

The above concerns lead us to elaborate on some key ideas to understand the provisional and emergent ways in which technology-rich data-driven decision processes for actionable insight are accomplished. To adequately consider how decisions arise in heterogeneous relationships that involve humans and technology contributions, we need theoretical perspectives that go beyond the

traditional dualisms, such as hard-soft and human-nonhuman. Indeed, hybridity is emerging as a core concept across a number of literatures to overcome the categorical distinction between human decision-makers and technology. The radical move of these theories is that they efface traditional analytical distinctions, e.g. between agency and structure or the micro and the macro, and instead consider how phenomena arise through the relations of heterogeneous elements. In other words, hybrid theories advance more integrative notions and approaches that help us inquire into how decision-support and advanced technology may be understood jointly. As such, hybridity appears relevant to the growing scholarly interest in understanding the potential contribution of technology-rich data-driven decision support to OR practice (cf. Cordoba & Midgley, 2008; Munro, 1999; Ufua et al., 2018), where actions are formed and are given meaning in relationships with human actors and (boundary) objects (Franco, 2013; Hazen et al., 2016; White, 2009). With this interest to understand OR practice we highlight some ways of conceptualising hybrid relationships that have emerged in the literature.

Theories of hybridity emphasise the connected and hybrid quality of human-technology practice and encourage thinking about how decisions arise from the relations between technology, processes, values, interests and beliefs (Knorr-Cetina et al., 2005; Orlikowski, 2000). To enable nuanced considerations of hybridity in OR in the context of technology-rich data-driven environments, we consider three different theoretical perspectives: Actor-Network Theory (Latour, 2007), Sociomateriality (Orlikowski, 2009) and Cyborgs (Haraway, 1985, 2014) (Table 1). While hybrid theories have been used to inform work in a wide range of disciplines, including information systems (Cecez-Kecmanovic et al., 2014; Orlikowski, 2006), organisation studies (Nyberg, 2009), geography (Atkinson, 2005), and engineering (Kaghan & Bowker, 2001), they have also been previously considered in OR work (Table 1). In considering the 'common element' of these hybrid theories, it appears that all three theories have relational ontologies (Table 1). These posit that technical, material and social forces bring forth everyday activities and entities. However, there are differences between the theories in the degree of integration and separability of the elements. In Actor-Network Theory, what actors are and do is the effect of their relations with other actors (Latour, 2007). As such, Actor-Network Theory assumes that social and material elements interact but have an existence on their own. Sociomateriality, on the other hand, assumes that the entanglement of the social and material is necessary for a sociomaterial phenomenon to arise, i.e. the different elements are said to intra-act in a performative manner. In other words, heterogeneous material, technological and human elements act together to bring about what then appear to be actors and phenomena that we experience (Barad, 2007). Finally, the Cyborg perspective assumes a much greater integration of

different elements, inspired by biological metaphors and cybernetic organisms. In the following sub-sections, we provide further detail on our three theoretical perspectives. The theories use specific terminology to refer to units of analysis that consider relations between humans and nonhumans (Table 1), which is explained further in the subsequent paragraphs.

Table 1 Theoretical perspectives on the intertwining of technology and humans in decision processes

	Actor-Network theory	***Sociomateriality***	***Cyborgs***
Focal concepts	Socio-technical assemblages	Material-Discursive practices	Cybernetic organisms
Ontology	Anti-essentialist	Agential realism	Companion species
Key works	Latour, 2007	Orlikowski, 2009	Haraway, 1985, 2014
The process of establishing connections	Socio-technical Interaction	Intra-action and Performativity	Integration/Sympoiesis
OR examples	White, 2009	Franco, 2013	Taket & White, 1997
OR application areas	Opening the black-box of problem structuring interventions	Understanding interaction with models	Catalysing collective local action

2.1 Actor-Networks and Assemblages

Latour's Actor-Network Theory (ANT) employs the metaphor of assemblage (Latour, 2005) to express how configurations of human and non-human elements arise. The concept of an assemblage emphasises durable and seemingly irreversible ties (Law, 1992) between humans and nonhumans. ANT then draws attention to the mobilisation of interests, goals, and identities as these assemblages are created and changed. Therefore, the assemblage metaphor can be used to inquire into recursive relationships of multiple human decision-makers and technologies that shape each other. The core tensions in this theory allow us to inquire into those between, on the one hand converging, stabilised and irreversible formations and on the other hand the potential for change arising from processes of problematisation, engagement and mobilisation (Callon 1986; White 2009). An insightful application of ANT for OR has been presented by White (2009). In the context of decision processes, this theory calls upon decision-makers to recognise that what they may believe to be unquestionable 'matters of fact' might be better understood as 'matters of concern' (Latour, 2004). In other words, the belief in proof through objective facts is questioned because the socio-technical processes by which these 'facts' come into existence are much more subjective than is traditionally acknowledged. Specifically, Latour called for an examination of the historical, local, connected, uncertain and variegated processes of the production of facts – or matters of concern (Latour, 2005a). As such, ANT encourages

us to inquire into the collective decision processes and question how, instead of assuming autonomous action may be taken based on facts and truth, we can enable the exchange of assertions in hybrid forums which reach socially negotiated approaches in the face of uncertainty, opacity and complexity (Latour, 2005a).

2.2 Sociomateriality and Entanglement

Sociomateriality focuses on relational dynamics between people and their environment. In this theory, the concepts of entanglement and performativity are used to inquire into these dynamics (Barad, 2003, 2007). The term entanglement suggests that the phenomena we observe are not decomposable into separate human and material entities. The term performativity refers to the way in which configurations of the social and material, when they occur in the form of material-discursive practices, have the capacity to accomplish action in the world (Barad, 2003). As such, technologies are not seen as independent of human agency, simply waiting to be appropriated. Rather, *"[H]uman agents build into technology certain interpretive schemes (rules reflecting knowledge of the work being automated), certain facilities (resources to accomplish that work), and certain norms (rules that define the organizationally sanctioned way of executing that work)*" (Orlikowski, 1992, p. 410). Hence, this view of sociomateriality (Orlikowski, 2006, 2007, 2009; Orlikowski & Iacono, 2001; Orlikowski & Scott, 2008, 2015) draws attention to people's repeated and situated interaction with particular technologies and how social behaviour is organised around and facilitated by (technological) objects (Niederer & Priester, 2016; Suchman, 2007). We find this perspective in OR studies which emphasise the relational aspects of sociomaterial entanglement with technology. For example, human-artefact interactions in OR workshops have been studied to understand how affordances of technology are realised in the process of creating (plans for) collective action (Franco, 2013; Franco & Greiffenhagen, 2018; Paroutis et al., 2015; White et al., 2016). These studies are concerned with the sociomateriality of decision structuring, focusing mostly on small- and micro-scale analysis of workshop interactions. While this research, which zooms into areas of practice, is highly insightful, it only partially captures the interrelationship of humans and technology in today's digital and network-mediated communication contexts. The core tension that this theory allows us to inquire into is between the conscious use of technology and its constitutive and performative role in our daily practices.

2.3 Cyborgs and Sympoiesis

Our third perspective draws on Haraway's theories of cyborgs (Haraway, 2013, 2016). Haraway's point is that, in increasingly technology-rich environments, it is no longer adequate to think about *the*

human decision-maker as a clear-cut biological human body. Instead, '*we are really bodies hooked into machines and bodies linked to other bodies by machines… There is no one 'cyborg' and no one benefit or drawback or evil'* (Grey et al., 1995, p.7). A cyborg is thus highly contingent and situated, and the specific relationship with technology needs to be understood in each case. As such, we need to find a way to understand situated knowledges and how many different technological, biological and cultural elements come together to co-produce decisions. Haraway refers to these integrative processes, in which together as *sympoiesis* (Haraway, 1988; Haraway, 2016).

In prior work in OR, the metaphor of the cyborg (Haraway, 1985) was found suitable to understand the collective generation, evaluation and elimination of options in local situations (Taket & White, 1997, 2004; White & Taket, 1997). Stimulating a process of inquiring into the influence webs in local problem contexts, the cyborg perspective (Haraway, 1990) has shown potential for informing OR practice which aims to realise the aesthetic, political and technical potentials in collective local action (Taket & White, 2004; White, 2006). However, today, decision-making activities are increasingly influenced by smart technology, such as wearables and smartphones. As such, the notion of the cyborg offers a potentially more important way of inquiring into associated decision behaviours (Lupton, 2015b; Haraway, 2016). The core tension that this theory thus allows us to examine is what it means to be a decision-maker when we are now highly connected, potentially leading to a spatially extended sense of self, and in a more complex role in wider networks. In other words, how do these extended and multiple ways of seeing oneself as a cyborg relate to a wider network of connections in a decision-making context?

In sum, the perspectives on hybridity appear to have great potential to help us inquire into the implications of increasingly technology-rich and data-driven decision environments for OR and vice versa. Specifically, we wish to study in depth the different notions of hybridity and the different decision-making contexts as they have changed with big data, data science and analytics. We present our methodology to approach this challenge in the following section.

3 HYBRID PRACTICE METHODOLOGY

Our theoretical perspectives on hybridity prompt us to keep an open mind about the dynamic relations between OR and technology-rich data-driven decision-making (Wilson, 2009). Our empirical approach aims to trace, in particular events or issues of professional practice, the forming of hybrid relations and why they persist and what work they do. We then aim to understand what characterises decision-making in these environments, so that we can reflect on the evolving nature of OR. Finally,

taking seriously that we live in an increasingly technology-rich data-driven environment implies that we also need to develop a hybrid research methodology (Lupton, 2015a, 2015b, 2017; Lewis et al., 2013). We, therefore, adopt a hybrid research approach that combines computational and human methods (Lewis et al., 2013). The benefits of combining computational-driven and human-driven analysis in a hybrid approach include that large data sets can be considered without losing the human ability to understand latent content for thematic categorisation (Sjøvaag et al., 2012). For large volumes of literature, computational approaches can help to reveal patterns through algorithmic analysis. The process of developing a deeper understanding, however, benefits from traditional methods that are sensitive to the socio-cultural contexts. As such, a hybrid approach appears increasingly suitable, as long as the unique human sensitivity to context is integrated into these approaches (Boyd & Crawford, 2012).

3.1 Constructing an Apparatus

Our analytical approach combines computer-assisted research and human interpretative phases. As such, our approach is aligned with our theoretical perspectives as we human researchers work with machines to extract, analyse and understand the socio-material 'body of knowledge'. The computer-assisted part allows us to undertake co-occurrence mapping of terms in a large body of literature to reveal key themes and topics by measuring the association strength of words (Monarch, 2013). As a software package for co-occurrence mapping, we chose VOSviewer (de Leeuw & van den Berg, 2011) because it is especially useful for intuitively displaying large co-word maps and also because the details about implemented algorithms are published (van Eck & Waltman, 2011). Resultant visualisations (e.g. Figure 1) show networked relationships between words by spatial proximity. Our human interpretative analysis consists of a qualitative inductive review of a set of core papers and book chapters that we identified with the help of this co-occurrence analysis.

Co-occurrence analysis aims to detect 'what's happening' and is similar to co-word analysis, a method championed in Science and Technology Studies (STS) since the 1980s (Callon et al., 1991; Callon et al., 1986; Courtial & Law, 1989; Law & Whittaker, 1992; Whittaker, 1989). Co-word analysis is well recognised as it allows for processes of identifying and displaying structural and dynamic aspects of research, showing linkages among subjects in a field and tracing emerging research areas (Benavides-Velasco et al., 2013; Bhattacharya & Basu, 1998; Börner et al., 2003; Callon et al., 1991; Ding et al., 2001; Moed, 2017; Muñoz-Leiva et al., 2012). This form of analysis has been shown to be a powerful technique that offers a significant approach to knowledge discovery (He 1999) and is an effective tool for identifying and revealing patterns underlying research fields (e.g. Hu et al., 2017; Leydesdorff &

Welbers, 2011; Ronda-Pupo et al., 2012).

Our approach contains three subsequent phases that build on each other. First, we generated a corpus of relevant literature through a Scopus search, then we undertook co-occurrence mapping and identified a set of core papers. The detailed steps that we undertook in the analysis stages are provided in the online appendix to this paper to allow readers to implement the methodology themselves. Lastly, we undertook a qualitative review and present the findings in section 4.

3.2 Search Process and Results

To undertake a co-occurrence analysis, it is necessary to identify a corpus of existing literature that can be mined for co-occurring terms or topics. Driven by our theoretical perspectives on hybridity and the focus on actionable insight for decision-makers, we constructed the following search query that we submitted to Scopus:

(ALL ("decision-making") OR ALL ("decision support") OR ALL ("decision aiding") OR ALL ("decision process")) AND (ALL (analytics) OR ALL ("big data") OR ALL ("data science")) AND (ALL (cyborg) OR ALL (sociomaterial) OR ALL (assemblage) OR ALL (actor-network) OR ALL (sociomateriality) OR ALL (Latour) OR ALL (Haraway) OR ALL (Orlikowski))

The Scopus search returned 1024 results, of which we exported bibliographic details. We then imported these into VOSviewer and ran a co-occurrence analysis of the authors' keywords. Of the 2791 keywords, and a suggested minimum number of occurrences of a keyword of 5, 64 keywords met the threshold. We removed keywords that pertained to standard research methodologies (case study, taxonomy, literature review) as well as those keywords that we had included in the original search query (big data, analytics, actor-network [theory], data science, decision-making), such that 56 keywords remained for the visualisation. VOSviewer's clustering algorithm was then run on the remaining keywords, and Figure 1 shows the results from the co-occurrence analysis of the main corpus. As the visualisation of the results from the co-occurrence mapping (Figure 1) relies on colour to display the different clusters and the printed journal copy is monochrome, the co-occurrence map (Figure 1) is available for download in the digital appendix. It is available in the Graph Modelling Language (GML) file exchange format, which can be explored using VOSviewer, or any other tool capable of displaying it. In addition, we present all the terms contained within the clusters in Table 2.

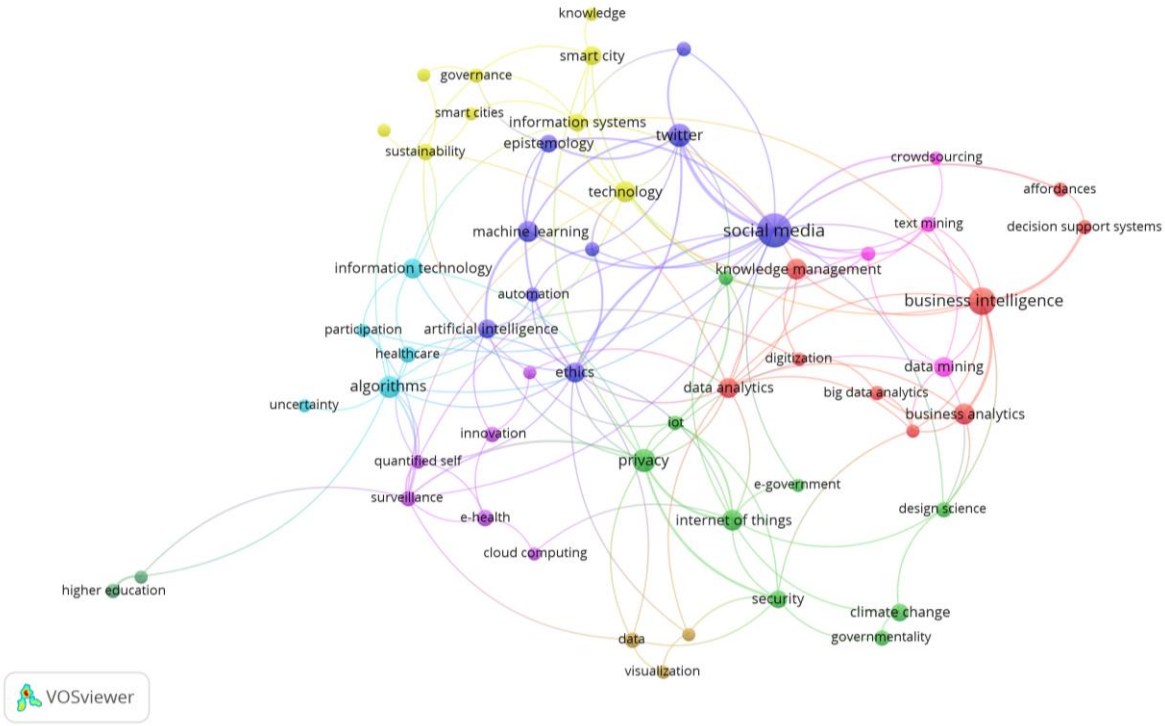

Figure 1 Keyword Co-occurrence Analysis (Large visualisation available in the digital appendix)

Table 2. Overview of clusters

Cluster 1 (red) *Business decision support systems*	**Cluster 2 (green)** *Digitalising public and private decision infrastructures*	**Cluster 3 (blue)** *Meaning making in digital engagement*
affordances big data analytics business analytics business intelligence business value data analytics decision support system digitization knowledge management	climate change design science e-government fuzzy logic governmentality internet of things iot (Internet of Things) privacy security	artificial intelligence automation epistemology ethics internet machine learning social media social network analysis twitter
Cluster 4 (yellow) *Digitally-augmented environments*	**Cluster 5 (purple)** *(Self-)quantifying performance practices*	**Cluster 6 (turquoise)** *Changing loci of decision responsibilities*
governance information systems interdisciplinarity knowledge	cloud computing e-health energy efficiency innovation	algorithms healthcare information technology participation
Cluster 7 (pink) *Digital knowledge generation*	**Cluster 8 (amber)** *User interface considerations*	**Cluster 9 (olive)** *Education*
crowdsourcing data mining sentiment analysis text mining	data risk management visualization	higher education learning analytics

While we have proposed inductively derived titles for the clusters based on the keywords within each cluster (Table 2), a more in-depth study of the content contained within the clusters is needed for meaningful insight. Therefore, we identified the key papers contained within the results of the co-occurrence analysis (Figure1, Table 3) by cross-referencing the keywords in the clusters with the authors' keywords in the data exported from the Scopus query. We then sought to identify the set of papers which had keywords in the highest possible number of clusters, which resulted in 18 core papers which were tagged with keywords that occurred in at least three different clusters. Table 3 presents an overview of these papers and thereby also illustrates the breadth of disciplines represented.

Table 3. Set of core papers derived from the co-occurrence analysis

1	Abbasi, A., Zahedi, F. M., Zeng, D., Chen, Y., Chen, H., & Nunamaker Jr, J. F. (2015). Enhancing predictive analytics for anti-phishing by exploiting website genre information. Journal of Management Information Systems, 31(4), 109–157.
2	Ananny, M. (2016). Toward an ethics of algorithms: Convening, observation, probability, and timeliness. Sci. Technol. Human Values, 41(1), 93–117.
3	Calvard, T. S., & Jeske, D. (2018). Developing human resource data risk management in the age of big data. International Journal of Information Management, 43, 159–164.
4	Carah, N. (2017). Algorithmic brands: A decade of brand experiments with mobile and social media. New Media & Society, 19(3), 384–400.
5	Çifci, H., & Yüksel, N. (2018). Foresight 6.0: The New Generation of Technology Foresight. In 2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC) (pp. 1–5). IEEE.
6	Cresswell, K. M., & Sheikh, A. (2017). Inpatient Clinical Information Systems. In Sheikh, A., Bates, D. W., Wright, A., & Cresswell, K. (Eds.). Key Advances in Clinical Informatics: Transforming Health Care Through Health Information Technology. (pp. 13–29). Academic Press.
7	Limburg, D. (2014). Social Innovation through Information Provision. In Human Resource Management, Social Innovation and Technology (pp. 21–36). Emerald Group Publishing Limited.
8	Liu, S. M., & Yuan, Q. (2015). The evolution of information and communication technology in public administration. Public Administration and Development, 35(2), 140–151.
9	Luo, X., Zhang, W., Li, H., Bose, R., & Chung, Q. B. (2018). Cloud computing capability: its technological root and business impact. Journal of Organizational Computing and Electronic Commerce, 28(3), 193–213.
10	Lustig, C., Pine, K., Nardi, B., Irani, L., Lee, M. K., Nafus, D., & Sandvig, C. (2016). Algorithmic authority: the ethics, politics, and economics of algorithms that interpret, decide, and manage. In Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems (pp. 1057–1062). ACM.
11	Marzouki, A., Mellouli, S., & Daniel, S. (2017). Towards a context-based Citizen Participation Approach: A literature review of citizen participation issues and a conceptual framework. In Proceedings of the 10th International Conference on Theory and Practice of Electronic Governance (pp. 204–213). ACM.
12	Mendes, R., & Vilela, J. P. (2017). Privacy-preserving data mining: methods, metrics, and applications. IEEE Access, 5, 10562–10582.
13	Mittelstadt, B. (2017). Ethics of the health-related internet of things: a narrative review. Ethics and Information Technology, 19(3), 157–175.
14	Prinsloo, P. (2017). Fleeing from Frankenstein's monster and meeting Kafka on the way: Algorithmic decision-making in higher education. E-Learning and Digital Media, 14(3), 138–163.
15	Rocha Filho, G. P., Mano, L. Y., Valejo, A. D. B., Villas, L. A., & Ueyama, J. (2018). A low-cost smart home automation to enhance decision-making based on fog computing and computational intelligence. IEEE Latin America Transactions, 16(1), 186–191.

16	Sharon, T. (2017). Self-tracking for health and the quantified self: Re-articulating autonomy, solidarity, and authenticity in an age of personalized healthcare. Philosophy & Technology, 30(1), 93–121.
17	Troisi, O., D'Arco, M., Loia, F., & Maione, G. (2018). Big data management: The case of Mulino Bianco's engagement platform for value co-creation. International Journal of Engineering Business Management, 10, 1847979018767776.
18	Wu, J., Guo, S., Li, J., & Zeng, D. (2016). Big data meet green challenges: big data toward green applications. IEEE Systems Journal, 10(3), 888–900.

Next, we accessed the full-text of these papers and book chapters. Specifically, we sought to understand how the results relate to hybridity in OR work. Through reading and re-reading, i.e. through an inductive matching process, we identified the most relevant theoretical perspectives for each result.

4 FINDINGS

The reviewed papers have in common that they consider how the introduction of technology changes decision practices. Many share the understanding that the potential of technological developments needs to be understood in relation to social and organisational capabilities (Ananny, 2016; Calvard & Jeske, 2018; Luo et al., 2018; Lustig et al., 2016). A number of papers focus specifically on algorithms (Ananny, 2016; Carah, 2017; Lustig et al., 2016; Prinsloo, 2017) and how they change what we pay attention to by what they measure and visualise (Lustig et al., 2016), and how algorithmic decision processes modify the infrastructure for decision-making (Wu et al., 2016). In this context, some authors convey a sense of an inescapable entanglement of humans in algorithmic systems (Ananny, 2016; Lustig et al., 2016; Prinsloo, 2017). As such, they call for an active questioning by human decision-makers of decision recommendations produced by analytics systems. This highlights the need for greater awareness of the issues faced by human decision-makers and suitable approaches to managing the uncertainties and risks that might arise (Calvard & Jeske, 2018). To gain better insights into the implications for decision-support, we consider the papers in more detail through the three theoretical lenses of hybridity: cyborgs, sociomaterial performativity and assemblages.

4.1 Sympoietic Cyborgs

What is striking from some of the papers examined is that there is a clear sense of the collectively produced cyborg becoming an increasingly appropriate way of conceptualising how the growth of sensors and the internet of things (IoT) leads to the adaptation of daily routines (Sharon, 2017). This notion of the cyborg gains a sense of self through the quantification of human activities by technological devices, delivering insight which can then be used towards enhancing human performance (Sharon, 2017). Wearable sensors, self-tracking devices and mobile applications could engage human decision-makers in a similar way through the collection of data about themselves, creating a quantified indication of the users' behaviour, thought patterns and even vital signs. Not

surprisingly, we find from the papers we studied that there is a growing interest in the potential of such self-tracking practices in healthcare insofar as these may prevent ill-health, improve diagnostics and engage patients in their own recovery (Mittelstadt, 2017; Sharon, 2017). It is, however, not just within health that such technologies are of interest. Rather, they are becoming more relevant for measuring the performance of, for example, employees, and therefore may raise some fundamental questions (Lustig et al., 2016; Sharon, 2017). Specifically, when the logic of self-enhancement becomes blurred with a logic of enhancement of the value-driven activity undertaken for others, e.g. an organisation (Lustig et al., 2016), more controversial effects arise (cf. Lupton, 2012, 2014 cited in Sharon, 2017). On the one hand, self-monitoring devices may enable participatory and personalised measurements or ratings of performance which allow individuals to make a claim to the value of their activities and even their work. On the other hand, such use of the aforementioned devices potentially has disempowering effects as performance becomes depersonalised and decontextualised in the form of numbers (Lustig et al., 2016; Mittelstadt, 2017). Moreover, as measurement is never entirely neutral (Lustig et al., 2016; Prinsloo, 2017; Sharon, 2017), it is necessary to consider what it means when the ideals of 'good performance' are programmed into devices which then demand conformity with norms and adherence to these pre-set standards (Sharon, 2017). As such, as we reviewed these articles, a number of fundamental questions arose pertaining to the decision-makers' shared understanding of autonomy and authenticity (Sharon, 2017) and whether individuals will and should accept the growing underlying sense of self-responsibility (Mittelstadt, 2017). In other words, decision behaviours arise through a 'making-together-with' (sym: together-with, poiesis: making) of tracking and sensing technology and the traditional boundaries of the human body. For example, 'healthy behaviour' becomes a collective accomplishment of human-technology cyborgs, as the tracked indicators of the state of (ill-)health become visible and can be acted upon by programmable devices, e.g. once a threshold is met. Such strategies for target attainment – be it health or worker performance – can then be thought of as being pursued sympoietically. Questions that arise for OR decision support in a cyborg sense in relation to the adoption of self-tracking technologies in organisational contexts are presented in Table 4.

Table 4. Guiding questions for OR from the Cyborg Perspective

Guiding questions for OR practice
1. How can the capability of decision-makers who are entangled with advanced (tracking) technology be enhanced in ways that enable them to challenge the measurement schemes that their data are subjected to and which in turn will influence their sense of self?
2. What should the relevance for decision-making be of accounts of subjective lived experience versus quantified and tracked data about the experience?

3. How can intended collective performance measures, such as organisational effects, be related to individual behaviour, that may be more narrowly tracked and measured?
4. What are the limitations of individual-level tracking data for understanding collective work practices and team/organisational performance?
5. How can OR practitioners facilitate an informed group decision-making process that considers threats and opportunities to autonomy, solidarity and authenticity (Sharon, 2017) in relation to (self)tracking technology?

Next, we consider questions arising for material-discursive practices specifically in organisational contexts suggested from the review of the results.

4.2 Sociomaterial Practices

The papers we examined presented optimistic views of the potential to enhance collaboration and (social) innovation through the introduction of digital technology in organisational decision processes (Limburg, 2014; Luo et al., 2018). They emphasise how the infrastructural features of the technologies enhance capabilities for value-adding human-to-human collaboration. Specifically, we found that the articles emphasise the potential for creating social communication networks and transparency. (Limburg, 2014; Troisi et al., 2018). Not unrelated we also found advances in technologies to support distributed decision-making, particularly in the public sector (Çifci & Yüksel, 2018; Liu & Yuan, 2015; Marzouki et al., 2017). The papers suggest that well-known related challenges are the need to study the interplay of social and technical factors when considering effective implementation and adoption strategies (Cresswell & Sheikh, 2017). Overall, however, these findings emphasise the infrastructural and mediating nature of technology rather than specifically focusing on the performativity with technology (cf. Orlikowski, 1991 cited in Limburg, 2014).

Considering organisational decision practices, Calvard and Jeske (2018) argue that the allure of seemingly complete analytics systems' recommendations might lead generalist managers to jump to action and skip the human interpretative process together with specialist expert staff (Calvard & Jeske, 2018). Specifically, Calvard and Jeske suggest that there is a need to develop the skill to question the completeness of underlying models and maintain a critical distance, leading to further interpretation, before decision-makers act upon recommendations from analytics. Their concerns echo the automation vs augmentation debate in the workplace in general.

A particular feature arising from our examination of the papers which provides a good example of entanglement in relation to the marketing function of an organisation is algorithmic branding (Carah, 2017). We feel this is a good example of sociomaterial performativity (Troisi et al., 2018). This concept refers to organisations designing digital and interactive environments through which they engage customers in affective and immersive experiences. The data that is generated in this way goes beyond

descriptive data about customers towards the 'active' co-creation of product innovation in digitally-mediated affective experiences (Troisi et al., 2018). As such, technical brand value arises through purposefully designed sociomaterial experiences (cf. Ramaswamy & Ozcan, 2016 cited in Troisi et al., 2018). This is of particular relevance to OR as marketing is a fast-growing area at the interface of OR with other disciplines (Jin et al., 2017; Karray & Martín-Herrán, 2018; Nalca et al., 2018; Pnevmatikos et al., 2018; Torres & Bijmolt, 2009; Zhang et al., 2018). Relatedly, Carah (2017) traces how culturally embedded, and participatory forms of branding have become integrated with the predictive and analytic capacities of social media, which is of relevance to OR (Chen et al., 2015). However, with the emergence of data-driven technologies, Carah argues that the logic of participation has shifted (cf. Arvidsson & Peitersen, 2013 cited in Carah, 2017). This example of entanglement, for us, indicates that organisational decision practice now operates "*at the intersection between data, the cultural-symbolic and (media) materiality*" (Brodmerkel & Carah, 2017, p.61). This is also reflected in OR research, for example in the area of behaviour-aware user response modelling in social media to influence purchase decisions of customers (Chen et al., 2015). As such analytics are not just abstract computational processes, but also shape human actions with limited human control (Prinsloo, 2017). Accordingly, the need for human oversight, regulation, accountability and transparency of algorithmic decision-making is emphasised (Prinsloo, 2017).

Questions arising for OR decision support in relation to the entanglement in advanced analytics systems are detailed in Table 5.

Table 5. Guiding questions for OR from the Sociomaterial Performativity Perspective

Guiding questions for OR practice
1. How can the capability of human decision-makers be supported to challenge the potentially flawed assumptions underpinning the 'optimal solution' provided by analytics software? (Cf. Calvard & Jeske, 2018)
2. How can holistic and dynamic models of advanced analytics systems be developed that consider the recursive relationship within evolving organisational capabilities? (Cf. Luo, 2018; Cresswell & Sheikh, 2017; Calvard & Jeske, 2018)
3. When conceptualising agency of human decision-makers in models, what influence can human decision-makers be thought to have when their contributions are becoming part of a larger system of automated decision-making? (Cf. Lustig et al., 2016)
4. How do OR analysts need to (re)conceptualise their understanding of informed decision-making capability when individuals' choices are entangled in digitally-mediated social experiences?
5. How can OR practitioners support individuals to become aware of how they become entangled in social relationships online so that they can recognise the purposefully designed nature of the engagement?

Lastly, we consider our search results through the lens of the socio-technical assemblage.

4.3 Socio-technical Assemblages

As we have stated earlier, the assemblage lens is particularly suitable for understanding infrastructural systems (Abbasi et al., 2015; Mendes & Vilela, 2017; Rocha Filho et al., 2018; Wu et al., 2016), as well as wider ethical concerns (Ananny, 2016) pertaining to such socio-technical systems in which multiple organisations tend to be implicated. As assemblages are seen to emerge out of the reinforcing relationships among elements that can themselves exist as separate entities, the concept can thus integrate the inherently dynamic and multi-faceted nature of large-scale infrastructures. As such, it could be usefully applied to explore in depth the references to smart utility infrastructures (Wu et al., 2016), in which big data technologies may be coupled to achieve sustainable development objectives (Wu et al., 2016). Relatedly, high-tech systems for privacy and security (Abbasi et al., 2015; Mendes & Vilela, 2017), and the relationships of humans in interaction with smart technology constitute examples of challenges arising in increasingly digital-data rich socio-technical assemblages (Abbasi et al., 2015). While assemblage thinking could be applied to each of these to understand decision support challenges, here we consider its generic relevance for decision support practices. A fundamental question pertaining to decision-making in assemblages is posed by Ananny (2016, p.94), who asks: "*what might it mean to take an algorithmic assemblage—a mix of computational code, design assumptions, institutional contexts, folk theories, user models—with semiautonomous agency as a unit of ethical analysis?".* By focusing attention on the question how an assemblage acts, Ananny (2016) proposes an approach to an ethics that enable us to consider socio-technical relationships as they are established by algorithms that sort, rank, classify and categorise, recommend, optimise and open and close access to information. Specifically, he argues that we need to question an algorithmic assemblages' power by asking "*how are groups, similarities, and time lines governed by algorithmic assemblages creating (un)satisfactory relations*?" (Ananny, 2016, p.109). Table 6 identifies questions that pertain to decision-making in assemblages related to dimensions of OR practice.

Table 6. Guiding questions for OR from the Assemblage Perspective

Guiding questions for OR practice
1. How should decision-makers reconcile the potential for algorithmic learning from its environment (cf. Mendes & Vilela, 2017; Rocha Filho et al., 2018)?
2. How can decision-makers develop a better understanding of behavioural elements that influence how human decision-makers interact in (un)safe ways with big data technologies (cf. Abbasi et al., 2015)?
3. How can decision-makers understand the options for distributing authority among the diverse socio-technical actors in algorithmic assemblages (cf. Lustig et al., 2016)?
4. How can decision-makers jointly debate what constitutes satisfactory relations between humans, objects, technologies, policies and ideas such that we can intervene in algorithmic assemblages (cf. Ananny, 2016)?

5 DISCUSSION

"Operational Research may be regarded as a branch of philosophy, as an attitude of mind towards the relation of man and environment; and as a body of method for the solution of problems which arise in that relationship."

(Kendall, Presidential Address to the Operational Research Society in 1958, cited in Beer, 1959).

As our organisational environments change, we need to re-examine and potentially adapt and refresh our OR practice. To support this process for environments that are increasingly characterised by big data, data science and analytics, this paper started out with the question: how can emerging technology-rich data-driven decision environments contribute to the practice of OR or vice versa? It was premised on the idea that there is very little discussion on data-driven decision environments and analytics dynamics and organisational challenges. In data-driven decision processes who will interact with whom or what and how will implementation of change take place?

A key implication arising from our work is the need for greater transdisciplinarity in OR research practice. Our findings suggest that no single discipline may be able to address the complex challenges arising for decision-support and decision-making in hybrid settings. The search results originated in the fields of engineering, sociology, information management, public administration, human factors, and philosophy of technology studies. The instantiations of hybridity covered application areas ranging from healthcare, marketing, human resources, smart homes, smart utility infrastructures, information technology security and e-governance and ethics. OR might be uniquely equipped to provide decision-support in such diverse contexts, as from its early stages it was conducted in multi-disciplinary teams (Churchman et al., 1957) and has increasingly not just embedded mathematics and engineering, but also psychology, knowledge management and ergonomics in its research and practice activities. It might, therefore, be the case that OR's unique offering in the context of technology-rich data-driven decision-making arises from its historical focus on decision processes and the 'strategy of assembly' (Beer, 1959), rather than content. It might thereby provide the integrative capability for different disciplines to work together in addressing the manifold challenges involved in realising value from big data, analytics and data science through OR. We now go on to describe the contribution of our research.

First, we make a methodological contribution to research practice in OR. Our approach in this paper is illustrative of a possible research practice in which analytics, algorithms and humans work together to gain insight into phenomena that would not otherwise be easily perceptible. The hybrid methodology that we have used in the co-occurrence analysis required us to go beyond our situated and embedded knowledge by using the algorithms of VOSviewer and search queries in Scopus. As

such, we introduced a hybrid approach to identify instances of the challenges involved in developing actionable insight in OR (cf. Royston, 2013).

Second, we advance theoretical developments in OR by taking forward three theoretical hybrid lenses to identify relevant questions for an OR research agenda in technology-rich data-driven environments. In this way, we believe the theoretical lenses on hybridity may be able to support OR-analysts and decision-makers in jointly developing actionable insights. We have sought to address this challenge with theories that consider the relational and processual aspects of activities, incorporating both human and non-human elements in their concepts and terminology. The subsequent review of the core search results has allowed us to develop a more nuanced understanding of the opportunities that big data, analytics and data science provide for OR and vice versa. Specifically, our findings have highlighted that the question is not whether we should engage critically with technology-rich data-driven decision-making but how this engagement can be accomplished (Prinsloo, 2017). For example, one of the key challenges that we identified pertains to the need to develop an engaged and active stance towards the growing authority of analytics (and algorithms) and the need to understand how collective agency is possible in increasingly individualised data systems (Ananny, 2016; Lustig et al., 2016). As such, we suggest that there is an opportunity for an integrative OR offering, which supports context-sensitive engagement processes with decision-makers. We develop this idea below.

By applying three different theoretical perspectives on hybridity, we have gained insight into human and non-human relations in technology-rich data-driven decision environments. Our findings have highlighted practical areas for development arising from the numerous open questions that pertain to the decision to develop, deploy and oversee technology-rich data-driven decision support processes in organisations. Table 7 shows a summary of our findings.

Table 7. Summary of findings

(The numbers correspond to the core papers that were included in the review [cf. Table 3])

Phenomenon	**Cyborgs**	**Material discursive practices**	**Assemblages**
	[13] Ethics [16] Self-tracking and quantified self	[17] Engagement for co-creation of value [10, 14] Ethics [5,7,8,11] Collaborative decision processes [6,9] Impact on performance	[12] Privacy [15] Automation [2] Ethics
Process	**Sympoietic becoming**	**Sociomaterial performativity**	**Socio-technical interaction**

As such, our findings suggest that the distinct processual logics of the three hybrid perspectives have their specific 'audience' of problems to which they can be effectively applied (Table 7). However, when

considering the findings in each perspective more carefully, what can we say about how the heterogeneous elements of, e.g. people, technology and processes are related? We thus review each perspective with its exemplars in turn.

The sympoietic cyborg perspective highlighted situatedness and contingency of the relationships of humans, materials and data. Our exemplars focused on how smart technology in and on the human body leads to the extension and distribution of the sense of self and how this changes how we judge whether we are (performing) adequately, related to decision-making, but also to personal areas such as health. We outlined that this raises tensions about the distribution of responsibility for action between the human-self and its augmented, extended cyborg which is acted upon by others, from without, based on its distributed data traces and in interaction with the technology that characterises it. As such, we can distinguish an irresolvable tension in how hybrid decision-making occurs through cyborgs between a concern for the self (internal) and influence exerted by others (external).

The sociomaterial practices perspective has drawn our attention to how decisions in organisations are the effects of the inseparable entanglement of humans with technology. This perspective, while emphasising the intra-action of humans and technology in theory, has – in our examples from the review – highlighted that this intra-action in practice appears to be interrupted, tentative, fallacious and bounded rather than systemic. Therefore, this perspective seems to contain the irresolvable tension between a ubiquitous technological infrastructure engulfing the decision-makers, and their struggles, in reality, pertaining to the use of technology.

The socio-technical assemblages perspective has helped us to focus on the ongoing integration of digital decision-making into infrastructure systems. On the one hand, our findings have emphasised the opportunities for sustainable development arising from such self-regulating infrastructures. On the other hand, however, they have raised the question about where the control for intervention in such systems should lie. For OR, the question arises: how can we facilitate collective deliberation about what constitutes satisfactory regulation of these systems? As such, we suggest that there is an irresolvable tension between the technical efficiency of system closedness and the social desirability of system openness.

In sum, each form of hybridity gives rise to a number of tensions in technology-rich data-driven decision environments. These tensions are at the heart of the most heated debates in the literature on technology-rich data-driven decision environments. We therefore now proceed to outline the basis for a framework which we call SMART OR.

5.1 The SMART OR Framework

We suggest that the relational and processual phenomena that arise when human decision-makers and big data, analytics and data science intertwine can be considered along a set of tensions, which we also outlined in Section 2, in which OR exists: i) internal vs external concerns, ii) openness vs closedness and iii) use of technology vs technical infrastructure. The aim of the framework is to facilitate the development of OR practice that may lead to actionable insights. The framework outlines that the theoretical perspectives may be used to provide different ways of viewing decision challenges (Figure 2).

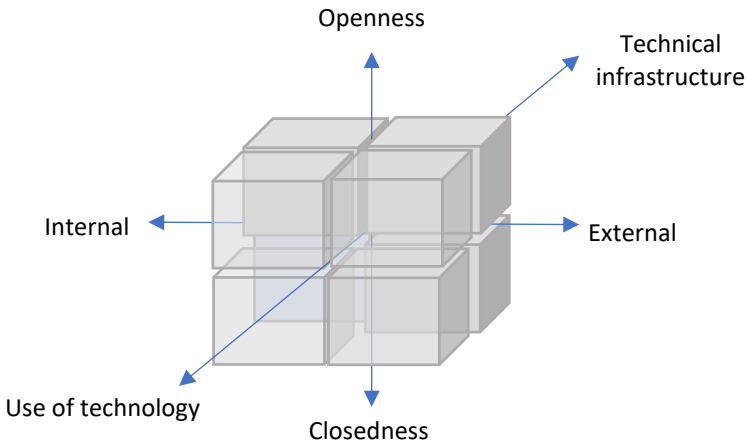

Figure 2 The SMART OR Framework

We thus propose the SMART OR framework (Figure 2), jointly with the guiding questions which we have derived theoretically and empirically through the review (Tables 4, 5, 6) for use by OR practitioners in participatory inquiry processes to develop actionable insight in technology-rich data-driven decision contexts. We consider the tension in each dimension in the following sections.

5.1.1 *Sympoietic Cyborgs*: *Internal-External*

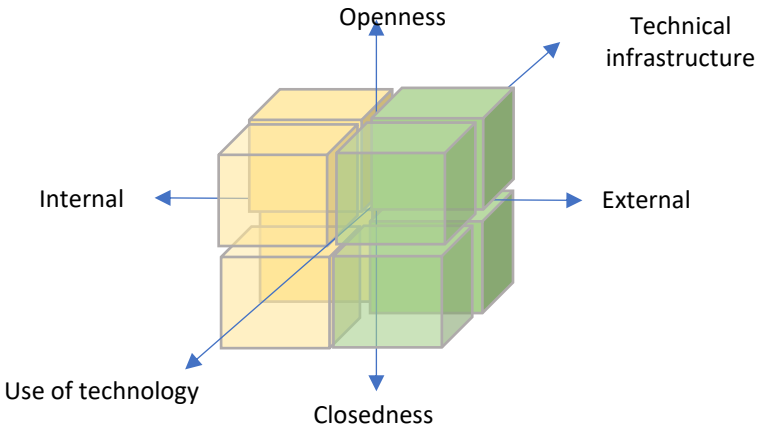

Figure 3 Cyborg boundary tension

From the tension between the use of smart devices for self-enhancement (internal concerns) and the increasing potential for managing decision-makers based on their data profile (external concerns) (Figure 3), we suggest that a growing need for analytics awareness arises. Recent research in OR is beginning to address this tension, e.g. through soft OR work which considers the importance of engaging stakeholders in developing approaches for managing this data profiling (cf. Small & Wainwright, 2018 for an example on electronic health records and role-based access control). Several areas for activity arise for OR practitioners. First, organisational decision-makers will need support in identifying what to measure, at what unit to measure and in understanding when automated measurement may lead to better decisions. Specifically, when considering strategic decision-making and creative innovation that is necessary for long term performance, is algorithmic insight based on data which learns only from the past the best source of information? When considering organisational development, is it beneficial to let individual staff compete against each other based on individual-level tracking devices when we still do not fully understand how social and collective interaction accounts for performance in today's organisations? In other words, we suggest that OR practitioners may need to facilitate the development of analytics awareness about these qualitative, strategic questions.

5.1.2 Sociomaterial Practices: Use of Technology – Technical Infrastructure

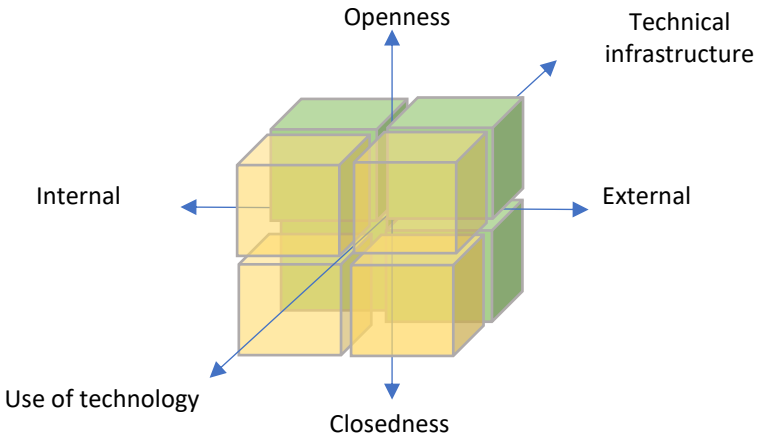

Figure 4 Sociomaterial agency tension

From the tension between the need for a ubiquitous infrastructure as part of the increasing digitalisation of all organisational processes (technical infrastructure) and the need for sensible, purposeful and possibly selective use of technology in strategic decision-making (use of technology), we suggest that the need for more integrative modelling arises. Specifically, we mean models which help decision-makers consider how technology is (un)productive in co-creating value. Work in OR which considers the challenges of integrating technology for enhanced performance and the proficient and sensible use of high performing systems is emerging (e.g. Pape, 2016) and the fine line between value and ethics, particularly from a user's point of view has also been previously highlighted (Vidgen et al., 2017). Several areas of activity arise for OR practitioners. First, organisational decision-makers may need support in understanding the indirect and mediated relationships between advanced infrastructure and organisational performance. For example, assessing the impact of introducing analytics may need to occur at the level of organisational processes before any assumption about its effect on organisational level performance can be made (Aydiner et al., 2019). Second, these assumptions about the impact of potential business process changes on the overall organisation's ability to make decisions in a more flexible and agile way, need to be assessed. To support these processes, traditional OR approaches such as system dynamics and discrete event simulation, but also agent-based modelling may prove increasingly useful to help decision-makers develop their own understanding of the potential of analytics technology for their organisation.

5.1.3 *Socio-technical Assemblages*: *Openness – Closedness*

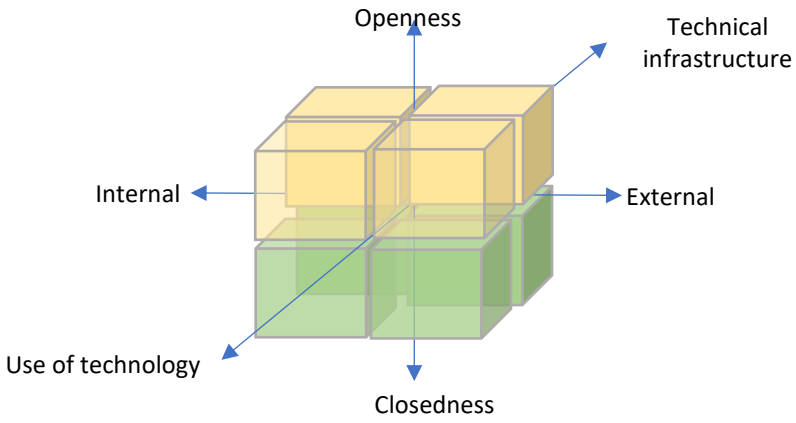

Figure 5 Assemblage transformability tension

From the tension between the desirability of openness and responsiveness of technical systems to human intervention (openness) and the technical efficiency of a self-optimising system (closedness), we suggest that the need for deliberation arises (Figure 5). Specifically, this dimension highlights a challenge arising from the obscurity and inscrutability of analytics, i.e. that access to the formulation of analytics tends to be closed as they are proprietary and that they tend to be embedded within wider socio-technical assemblages. They are therefore difficult to unpack (cf. Kitchin, 2017; Ziewitz, 2015). An open counter position is a pluralism (Johnson, 2014) that encourages the participatory development of an open system by including those who give up, analyse and derive value from data, who, in an organisational environment may be the different department heads, the analytics support function and the directors (Johnson, 2014; Donovan, 2012). Opening up real-time data about departmental performance within an organisation more widely may potentially lead to new insights, more joined-up thinking and the identification of cross-programme or cross-departmental efficiencies (cf. Kitchin, 2014). However, the associated changes to organisational reporting and knowledge management policies and the behaviour changes that 'trusting' others with one's department's live data involves, may need to be negotiated with the different department heads. Invariably, the development of systems where openness is not just a technical term but includes openness to shared analysis and insight from data requires deliberation. Thus, we suggest that traditional Soft OR interventions may still be a suitable response to the different viewpoints that practitioners need to consider in such decision-making challenges (Eden & Radford, 1990; Friend & Hickling, 2012).

In sum, drawing together the theoretical, methodological and practical contributions, our proposal for

a SMART OR calls upon practitioners to adopt a reflexive approach to understanding the co-implications of human-technology connectivity. For example, when human choice is eliminated by technology that is authorised, by the processes in which it is embedded, to modify or constrain options available to humans, the framework serves to remind the OR practitioner to consider ways of co-creating deliberative exchanges. By considering the implications of technology-rich data-driven environments for decision-making from different angles and perspectives, OR analysts may be able to help reveal how entities, people and technologies, their boundaries, properties and identities, are created and what the consequences are and for whom.

5.2 Limitations and Further Research

From a methodological point of view, one of the challenges of hybrid practice theories is that their application to real-world problems is still underdeveloped (Cecez-Kecmanovic et al., 2014). Therefore, as researchers, we need to become better at harnessing the increasing availability of data, which, for example, cyborg decision-makers create about themselves. Future research may involve the use of new methods such as (online) data trails to gain insight into the decision behaviour of people and their tools, in the moment, as well as across time and space. In this way, research that draws on big data may be useful for extending our sociomaterial theorising about decision-support as it may help us to understand 'the cyborg' rather than separate tools or techniques. Moreover, we need to consider how to understand responsibility and accountability in sociomaterial practices. In this context, it is timely to remember that "*Dr Frankenstein's crime was not that he invented a creature through some combination of hubris and high technology, but rather that he abandoned the creature to itself*" (Latour, 2011, p.11). We have sought to make a start to address this challenge with our SMART OR framework and the guiding questions tables. While these provide an operationalisation of the framework for OR practitioners today, more needs to be done to help decision-makers develop skills for the proficient engagement with data-rich decision environments. Specifically, our caveat is that practice is a mode of ordering, rather than an ordered product, an epistemology rather than an empirical phenomenon. A re-run of our search query that generated our corpus might reveal different instantiations and interfaces of hybrid phenomena as the database grows with new research. Consequently, no one corpus of literature constitutes a definite or complete representation of hybrid decision contexts, as this is evolving with our collective processes of knowledge production in this area. Therefore, the development of OR practice through the lenses of hybridity requires experimentation, improvisation, and critical thinking (Gherardi, 2012). Hence, this practice is related to the need to develop a better understanding of human behaviour, which is pursued through

Behavioural OR (Hämäläinen et al., 2013; Kunc, et al., 2016), but is grounded in a long history in OR of attempting to integrate sociological and psychological theories in its practice (Burgoyne, 1985; Cropper et al., 1989; Friend et al., 1988; Lawrence, 1966; Phillips, 1984; White 2016). Indeed, the current manifestation of Behavioural OR (e.g. Hämäläinen, 2015) can be seen as a resurfacing of these questions and as an acknowledgement of the need to revitalise and refresh the bases of OR engagements in the increasingly technology-rich decision environments. Similar ideas about the importance of thinking more deeply about human behaviour, for example in programming agent-based models or mitigate against biases as they influence participatory modelling, has also been developed in other fields (cf. Glynn et al., 2017; Tress et al., 2005; Voinov et al., 2016). Accordingly, transdisciplinary research opportunities are likely to be highly promising to further develop a SMART OR.

6 CONCLUSION

OR has flourished by supporting decision-making in times of relative information scarcity. In contrast, OR practice today is almost always performed in technology-rich data-driven environments. The role of OR in such contexts still needs to be defined. This paper envisions a SMART OR which identifies hybrid perspectives and hybrid methodologies as important considerations in developing contextualised approaches to creating actionable insight. We have suggested three theoretical perspectives that each offer different concepts and logics to understand how advanced technologies and human decision practices co-evolve. These theoretical perspectives may aid with developing awareness of multiple possible courses of action, distinguishing how decision-making arises in socio-technical relations and clarifying who is empowered to make decisions and how.

We propose the SMART OR framework that draws attention to and encourages the attending to the entanglement of actors in increasingly technology-rich and data-driven decision processes. Our framework has sought to capture forms of hybridity in which OR may support potentially collaborative decision practices. We offer the framework to support the exploration of context-specific opportunities for developing actionable knowledge, drawing boundaries around relevant socio-contextual information, including values and valuation. Engagement with the framework, which is aided by the derived guiding questions for a SMART OR that we have identified, may thereby facilitate the development of sounder decisions with the requisite model(ing) for actionable insights.

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