Chapter 9

Big Data and Behavior in OR: Towards a "Smart OR"

Leroy White, Katharina Burger and Mike Yearworth

9.1 Introduction

Recent decades have witnessed a new trend in Operational Research (OR) towards *Big Data* analytics (Davenport, Harris and Morison, 2007; Davenport, Harris and Morison, 2012), with the number of empirical studies steadily growing (Sen, 2013; Babai, Ali and Nikolopoulos, 2012). This trend complements traditional OR research (Ranyard, Fildes and Hu, 2015), which is dominated by mathematical/analytical approaches (Liberatore and Luo, 2010), and can help to address contemporary organizations/organizational needs (Singhal and Singhal, 2012). These needs are directly linked to new opportunities arising from the rapid development of digital technologies (i.e. the Internet and the internet of things), which enable researchers to collect valuable data online (see Google analytics for example). Unfortunately, these data are not always well-structured. On the contrary, online data generated by the end consumer are often qualitative and highly unstructured. As a result, OR researchers are hardly able to apply traditional approaches to utilise them. In order to analyse data collected on the Internet multiple methods are required which are able to explore the true value of online data.

At the same time, we also see a potential paradigm shift in operational research methods – and one that prompts new directions for research (Ranyard *et al*., 2015). The research contexts include human and managerial decision-making, consumer behaviour, operational processes and policy interactions. However, there is also a need to see a change in our ability to leverage approaches to achieve control and precision in data use, while maintaining realism in application and generality in theory development and practice. Thus: How can we take advantage of Big Data in OR? What new perspectives are needed? What will the new practices look like? What kinds of insights and value can they deliver in comparison to past developments? OR as analytics has broadened researchers' perspectives on social, organizational and policy systems, by adopting models that combine social science, OR, computer science and network science. This involves interdisciplinary fields that leverage capabilities to collect and analyse data with an unprecedented breadth, depth and scale.

Behaviour is now a key aspect in Big Data analytics. A growing number of specialist companies search, mine and analyse Big Data for descriptive, predictive and prescriptive behavioural insights. They employ a combination of hardware, software and services to support decision-makers through visualisation and interpretation of data. Overall, the challenges in understanding Big Data and using derived insights to predict, prescribe or influence behaviour, suggest a need for co-design with groups of decision-makers that carefully weigh the opportunities and threats arising from the manifold and potential uses of Big Data technologies for organisational development and societal wellbeing.

In this chapter we wish to introduce the idea of SMART OR, where *it is the creative use of Big Data, hard and soft OR, the use of which enhances behaviour and positive results for decision-makers.* Thus, SMART OR should not only employ OR analysis techniques and/or the multiple methods of so called *Big Data* analysis, but also combine them with techniques which are well-known for their end-consumer empirical, and sometimes qualitative, data analysis (Mingers and Rosenhead, 2004), in particular those used in soft OR (Ranyard *et al*., 2015). Such multiple approaches will allow researchers not only to address the need to make use of online data, but also to understand behavioural insights through incorporating interdisciplinary knowledge into operational research Big Data analytics. Furthermore, the multiple approaches to Big Data analysis also allow researchers to respond to recent call for data driven research in the social sciences disciplines (Simchi-Levi, 2014). This chapter proposes a SMART OR approach for handling Big Data for exploring behaviour in decision settings.

9.2 Big Data and decision analysis

There is increasing belief that *Big Data* can transform society. By Big Data we mean proliferating and complex datasets that can be *open* or data shared online (McAfee and Brynjolfsson, 2012). We take the view that Big Data can be the source of new energy for social transformation and decision-making, and better private and public services (Schintler and Kulkani, 2014). The emergence of the diversity of the types of data available across the society offers new opportunities for organisations to show their worth. However, technical skills are needed to design and perform the complex analyses inherent in Big Data applications – but these skills alone will not unlock the full potential of Big Data. They need to be complemented with knowledge of the economic and social value of decision-making to translate the information into impact. However, the relation between value and impact must be viewed through the lens of *effective data use* for the empowerment of those marginalised from so called open data, i.e. not everyone has the requisite access or the necessary processing resources (Gurstein, 2011).

While there has been a growing interest in Big Data, interestingly, there are also countless organisations using and producing Big Data that are not just traditional IT companies. Many different organisations are also increasingly generating large administrative datasets and social media platforms. The combination of these different data sources, and in particular the linkage together of different data sets, provides both great opportunities and challenges to organisations. For example, by collecting data by novel means to track sentiments and/or beliefs, Big Data can help to facilitate social and civic empowerment and furthermore enhance and expand stakeholder participation in service development and delivery (Brabham, 2009). However, some thought must be applied to the question of how social media enforce certain processes or patterns of usage on their users thus *colouring* data. For example, current interest about the introduction of the "dislike" button in Facebook is prompting debate about the affordances offered by the social media platform and how the feature will be interpreted by its users. None the less, Big Data can be used to promote transparency and accountability, which in turn can engender trust between or within different stakeholder groups (Surowiecki, 2004). Thus, Big Data will increasingly play an important part in shaping the landscape of decision-making**.** However, while there is increasing enthusiasm for exploiting Big Data, and making better use of quantitative and qualitative data from a range of *open* and administrative sources, there is nonetheless a large gap between our understanding of Big Data and decision-making. Briefly, the benefits of Big Data speak more to improving description and prediction than strengthening the causal and explanatory knowledge that are crucial to decision analysis. Causal and explanatory knowledge are not obvious consequences of Big Data. But it is clear that Big Data can considerably thicken our description of service (for example using *Google Analytics*). However, it is by no means certain that the most effective users of Big Data, in terms of their impact economically and socially, will be motivated to seek explanatory knowledge from their exploitation of Big Data. Such use at best might be thought of as mere atheoretical pragmatism, where the benefits to the interpreters of Big Data feel justified in their actions. However, and more seriously, this pragmatism may elide with the emergence of a new instrumentalism exemplified by return to old ideas in new guises, for example Digital Taylorism (Brown and Lauder, 2012).

At the same time, many organisations are organising their activities in a variety of novel ways and collecting data on their services and activities, through social media, machine log data, sensor data and other forms of data collection that are different from the more formalised approach, where the majority of data collection has been through resource offline projects, based on surveys and field studies. In the social sciences, the tradition is very different. Clearly, new technologies are providing the opportunity to collect large amounts of passive data about what's going on as a society. Thus, as more and more interaction of the services with the client moves online, and organisations are collecting large amounts of big and open data as well as data from new sources (such as social media), the more there is a need to realise the potential in linking the novel forms of these data and outcomes. As Big Data become increasingly available and inexpensive, analytics will move from a field that relies predominately on collection of small data to one focused on both Big Data collection – identifying and extracting relevant data from public sources and leveraging technology to capture Big Data from people in a free living context – and on the development of new analytic methods to make sense of it all. However, Big Data from secondary sources are not likely to wholly replace new data collection.

There may also be some problems linking the data to decision-making. For some, Big Data sets seem to have limited use because of their irregularity and heterogeneity (Chen, Chiang and Storey, 2012). The data tend to be inherently biased and lead to a conclusion that contemporary statistical analysis routines are inadequate to examine them. But there are a number of things that offer hope. First, the type of information that may already be available could provide us with a large, diverse sample. Second, the dataset is rich and anonymous, it may be possible to look at issues across a wide range of variables. The issue of statistical significance takes on new meaning when working with thousands of data points. Unlike smaller studies, where considerable effort is expended to gather an adequate sample size, any large data set will allow a researcher to find a *statistically significant* result. We will be able to measure more variables across time, space and policy domains, describing better contexts in which organizational decision-making and service delivery takes place. By way of a summary, these data types may include:

- Consumed data created as a by-product of digital services;
- On-line data, e.g. social media, internet activity, web content, news feeds;
- Data from objects, e.g. satellites, machine logs, sensors;
- Actively supplied data, e.g. citizen reporting and crowdsourcing.

Whilst the excitement of achieving new levels of statistical significance is enticing, suitable care must be taken with the techniques used to analyse such data. Correlation is not causation may be a tired mantra but it does deserve further thought in an era where almost any data set can be analysed against any other. The "Spurious Correlation" web site[1] may be entertaining but does make a serious point. Without the intent to seek deeper explanatory models for data and with economic need driving pragmatic and purely instrumental approaches knowledge is withheld from

[1] http://www.tylervigen.com/spurious-correlations

wider scrutiny, not maliciously but through lack of interest in discovering it, leaving the interpretation of *better* purely in the hands of those able to access and analyse the data.

9.3 Big Data Analytics

Analytics is defined as the process of transforming data into insight for making better decisions. Chen *et al*. (2012) and others proposed a classification of Big Data analytics in three main sub-types:

i) *Descriptive analytics*: Where analysis is made to describe a past situation in a way that trends, patterns and exceptions become apparent. The first level of analytics explores what has occurred as a way to gain insight for better approaching the future, usually trying to answer the question of "what happened". At one level there is *data mining* that allows obtaining complex information from databases by aggregating multidimensional structures such as information cubes, where the data can be interrogated from different variables perspective. At another there is *visualisation*, which represent data into visual forms in order to enhance facts and patterns that may not be easy or feasible at all to identify in other formats.

ii) *Predictive analytics*: where analyses focus on real time and historical data to make predictions in the form of probabilities about future events. They are based on the machine learning techniques and other computational algorithms of data mining. Tools include: Regression (linear and logistic), Discriminant Analysis, Clustering and Dimensionality reduction.

iii) *Prescriptive analytics*: where analytics use predictions based on data to inform and suggest proposed sets of actions that can serve to take advantage or to avoid on a particular outcome. Prescriptive analytics are mainly associated with optimisation and simulation, and have special relevance in contexts of uncertainty relying on stochastic computational programming of random variables (e.g. Monte Carlo).

9.4 Big Data and Behaviour

The challenges in interpreting large amounts of data in general may be distinguished from the challenges encountered in decisions regarding the use of behavioural Big Data to influence behaviour. Behavioural OR has long been concerned with decision-makers' biases and limitations in dealing with ambiguity, information overload, pattern recognition and information relevance, to name but a few. On-going research in the fields of group decision-making and negotiation is thus relevant in the context of Big Data and behavioural OR. Furthermore, Ranyard *et al*. (2014) noted a lack of attention on soft OR and the Big Data analytics research. Soft OR offers methodological approaches of interest. Soft OR, with its demonstrated usefulness in facilitating group decision-making and development, may support decisions regarding the design of insight-generating behavioural experiments using Big Data platforms, such as social media, with the aim to understand how collective behaviour may be influenced.

To explore Big Data and behavioural OR we first highlight the behavioural challenges that decision-makers face when confronted with large amounts of data, and the role of behavioural OR in this context. Secondly, we discuss how behavioural insights from social media data may be used to *influence* collective behaviour and how organisations may benefit from the use of soft OR approaches in related strategy development.

9.5 Behaviour and decision-making with large amounts of data

Simon's work on satisficing and bounded rationality (Simon, 1955) has played a major role towards the development of behavioural OR. Simon's proposition was that people have a tendency towards satisficing rather than optimise when it comes to decision-making, whereby a decision is chosen which satisfies an individual's most important need, irrespective of whether the choice is ideal or desirable. Also, Simon contends that the ability for decision-makers to act rationally is dependent and bounded by the information he/she has access to and the computational capacity possessed. These processes time and time again bias the decision-maker towards certain types of actions or behaviours. By biases we mean a tendency towards a certain disposition. They are also referred to as systematic errors in judgement or heuristics (Kahneman and Tversky 1979; Kahneman, Slovic and Tversky, 1982; Gilovich, Griffin and Kahneman, 2002). Whilst there is a large stream of literature in this area, there is still a barrier to be overcome by decision-makers when faced or confronted with large amounts of data. This is because embracing data driven decision-making involves moving away from conventional decision-making processes. Concerns about cognitive limitations of decision-makers, and interactive modelling with groups, seem to have driven attention to the creation of methods of elicitation that require only ordinal judgements as inputs. Even more, this explicit concern with methods that are cognitively sound have been the basis for the proposition of decision analysis to take into account cognitive limitations of decision-makers in providing, processing and understanding information. With Big Data, we believe that there is scope for further discussion of these ideas. From a classical behavioural approach, the following would be the expectation in relation to decision-making and Big Data:

- *Information overload* is experienced at the point where decisions reflect a lesser utilization of the available information (Schroder, Driver and Streufert, 1967) or potentially useful information received becomes a hindrance rather than help (Jacoby, 1977). For example, there may be complications in distinguishing relevant information, difficulties in recognizing correlation between details and overall perspective, lengthier decision times, a disregard for large amounts of information and inaccurate decisions (Eppler and Mengis, 2004). It is not only the amount of information that determines information overload but also the specific characteristics of information, such as the level of uncertainty associated with information and the level of ambiguity, complexity, etc. Information overload can also be due to the characteristic of the decision-maker (e.g., personal skills, experience, etc.). In order to deal with too much information a decision-maker may stop searching once a satisfactory solution has been found; i.e. the satisficing heuristic (Buchanan and Kock, 2001).

- *Information relevance* is where the unstructured nature of Big Data might potentially result in the difficulty in choosing relevant data (see Davenport *et al*. 2012). There may be an exposure to excessive information that can lead to an inability to disregard irrelevant information. Excessive, hence irrelevant information reduces the decision-makers' ability to identify relevant information and consequently reduces decision-making performance. Finally, attention to irrelevant information has the potential to significantly limit the value that can be obtained from incorporating Big Data into the decision-making process.
- *Anchoring effect* is an often observed attitude that reflects a tendency to depend greatly on past performance and experience in decision making (Kaheneman *et al*., 1982). Anchoring, as a form of cognitive bias, may emanate from a common tendency to rely on prior information offered when making decisions. This may reflect an inertia that avoids risk taking, and may be costly in the long-run, in that decision-makers may forgo emerging opportunities.
- *Pattern recognition* is where Big Data provides the decision-maker with the ability to search for patterns in a large population of data that would otherwise be undetectable in samples or even smaller data sets (Baron and Ensley, 2006). Decision-makers can be vulnerable to various problems such as difficulty recognizing patterns of evidence, applying prior knowledge to current judgment task (see anchoring), weighing evidence inappropriately and combining information into patterns. It is clear that providing decision-makers with more contextual knowledge will improve their ability to accurately recognize patterns (suggesting soft OR).
- *Ambiguity* may arise from variations in the amount and type of information available, differences in the source reliability and lack of causal knowledge of observed events (Frisch and Baron, 1988). Unstructured data may be viewed as ambiguous and information ambiguity has been found to result in incorrect judgments. Individuals intolerant of ambiguity actively seek to reduce uncertainty by focusing on simple solutions and neglect additional information once a solution is identified (even one that is not optimal). Ambiguities that decision-makers encounter on stakeholder engagement affect their ability to accurately interpret evidence. In general,

ambiguity-intolerant decision-makers have been found to be less confident about rendering opinions on decision statements. Decision-makers intolerant of ambiguity will likely be uncomfortable with the unstructured nature of Big Data and as a result may avoid or downplay ambiguous information which could result in less than optimal judgments, leading to decreased overall effectiveness (due to ignoring information cues). However, the use of soft analytic tools may help decision-makers overcome ambiguity-related cognitive limitations.

In sum, the above endeavour to catalogue these tendencies in decision-making is conducted against an objective ideal of rational decision-making. Each of these tendencies or bias, as it is discovered through laboratory experiment, leads to further questions as to its prevalence and relative importance as a member of an ever-growing list. The approach to investigation and discovery is aligned with a variance-oriented epistemology (van de Ven and Poole, 2005) and is in effect following standard hypothetical-deductive method. The elimination, or mitigation, of these biases is then seen as the purpose of achieving appropriately detailed modeling (prediction) or experimental design (theory testing). However, the sheer quantity of biases discovered leads to enormous detail complexity in trying to eliminate them and thus raises the question as to the overall effectiveness of the approach. On the other hand, alignment with a process-oriented epistemology offers the opportunity to view collective decision-making from a perspective that

"...may incorporate several different types of effects into their explanations, including critical events and turning points, contextual influence, formative patterns that give overall direction to the change, and causal factors that influence the sequencing of events" (de Ven and Poole, 2005).

Here, the stages and/or types of decision-making can be investigated through a variety of approaches so long as the essential temporal nature of the process view is taken into account. The process ontology elides well with a focus on collective behaviour (White, 2015). Rather than the reductive and highly complex task of unpicking an exhaustive list of individual biases we can limit our investigations to accounts of what actually happens.

Big Data analytics providers have already developed sophisticated approaches for data capture, analysis and visualisation, employing hard OR techniques in the process. However, in all cases, a final step of human interpretation of data for specific problems, sectors and organisations remains. Specifically, challenges arising from Big Data for behaviour in decision situations potentially aggravate the problem that already exists with traditional data, where decision-makers are challenged with the interpretation of exceptions and anomalies (Chen and Zhang, 2014). Furthermore, whilst analytics applications may facilitate the identification of patterns, these still need to be made sense of in order to be *actionable patterns* (Hilbert, 2012*)*.

So far, the discussion has focused on facilitating the development of actionable patterns for organisational decision-makers using available Big Data. However, the reciprocal interactions between the behaviour of organisations that interpret Big Data and the behaviour of users who generate it have not yet been sufficiently considered. Organisations increasingly go beyond an internally-focused response to insights from Big Data and aim to proactively *influence* collective behaviour through the modification of the content that social media users are exposed to. The analysis of Big Data thus becomes a venture in nudging (or manipulating?) collective behaviour.

9.6 Influencing collective behaviour

Although many Big Data application areas involve predicting consumer behaviour in response to past behaviour and/or proposed interventions, relatively little attention has been paid to understanding the behavioural mechanisms at work. If, as suggested by Liberatore and Luo (2010) the analytics process is understood as consisting of a closed loop of data collection, analysis (predictive modelling and optimization), insight generation and action/implementation, then the link between insight and action is, arguably, the least well-developed of the links for Big Data, at least in terms of formal modelling tools.

Bentley, O'Brien and Brock (2014) provide an interesting account of the role of Big Data in the study of collective behaviour. They offer an analysis of social media data, e.g. from social network sites such as Facebook and Twitter, to tell us about how information flows throughout the large and complex network of human interactions. At the same time, decision-making often involves gathering information to determine the consequences of possible actions (Simon, 1955). Thus, we increasingly turn to search engines such as Google in particular, to provide information to support our everyday decisions.

Further studies have illustrated that online information gathering can also anticipate future collective behaviour. For example, Goel *et al*. (2010) demonstrated that search query volume predicts the opening weekend box office revenue for films, first month sales of video games and chart rankings of songs. Aside from search data, other research has provided evidence that the massive datasets generated by our everyday actions in the real world can also support better forecasting of future behaviour (King 2011). Big Data allow us to look for patterns in collective behaviour which might recur in the future, similar to the way in which we as individuals rely on the statistical structure we have observed in the world when trying to forecast consequences of decisions (Giguère and Love, 2013).

When considered at greater breadth, we argue in accordance with (Moat *et al*., 2014) that, in contrast to Bentley *et al*.'s conjecture, Big Data studies do far more than "allow us to see better how known behavioural patterns apply in novel contexts" (Bentley *et al*., 2014). Big Data offers us insight into information gathering stages of real world decision-making processes that could not previously be observed, while large-scale records of real world activity enable us to better forecast future actions by allowing us to identify new patterns in our collective behaviour (Moat *et al*., 2014). Such predictive power is not only of theoretical importance for behavioural science and operational research, but also of great practical consequence, as it opens up possibilities to reallocate resources to better support the wellbeing of society.

Another limitation of Bentley *et al*. (2014) proposed framework is the suggestion that decision-making can be understood along two dimensions. The first represents the degree to which an actor makes a decision independently versus one that is socially influenced. The second represents the degree of transparency in the payoffs and risks associated with the decisions actors make. In their response, Pfister and Böhm (2008) argue that "*Independence is fictional, and social influences substantially permeate preference construction*". They continue to state that "*in a big-data era, it will become a critical issue for decision-makers to select the appropriate mode […] from a dimension that runs from deliberate/emotionally complex to intuitive/emotionally simple"*.

Organisations are thus increasingly able to use the insights about behavioural dynamics in social media to influence collective behaviour through targeted campaigns using social media. For example, Facebook's "Voter Megaphone" campaign,

"*…which promotes voting by revealing the names and faces of friends who have already cast votes (and was portrayed to have increased voter turnout by some 340,000 in the 2010 US elections) has generated further controversy. While the promotion of voting appears to be a good use of social media, the fact that the Voter Megaphone project was also part of a study, and was thus only applied to certain users, raised ethical questions about the real world political impacts of this behavioural manipulation.[2]"*

In the UK, Facebook's "I'm a Voter"-button was introduced at the 2015 UK General Election. Similar campaigns have been conducted to increase registrations as organ donors and to encourage tax paying. Overall, new ethical, political and regulatory questions arise as soon as the passive reception of unstructured social media data from an organisation's environment is turned into a pro-active strategy that aims to change (or nudge) the behaviour of social media users by modifying the data they are exposed to.

[2] *https://changingbehaviours.wordpress.com/2015/02/18/behavioural-science-meets-data-science/)*

This leads us to argue that the ability of decision-makers to extract maximum value from social media data that is imbued with behavioural insight is highly dependent on their ability to ask responsible questions for interventions in these media, that would allow them to study local, potentially organisation specific, assumptions and hypotheses about collective user/customer behaviour in technology-rich societies. To facilitate the process of strategizing for creative and ethical intervention in media that generate Big Data, SMART OR practitioners are ideally placed as they can draw on a rich sources particularly when drawing on soft OR methods that consider the field's critical dimensions (Ormerod and Ulrich, 2014). Moreover, strategic systems thinking approaches, for example those that are intended to mitigate against unintended consequences through the establishment of iterative collaborative learning systems, such as Soft Systems Methodology, complemented by simulation approaches (e.g. Discrete Event Simulation, Systems Dynamics, Agent-Based Modeling) may prove valuable in the design of interventions in big social media environments.

9.7 Conclusion

We thus suggest a research agenda for SMART OR, where *it is the creative use of Big Data, hard and soft OR, the use of which enhances collective behaviour and positive results for decision-makers.* It is a multi-methodology approach that seeks to facilitate the emergence of distributed agency towards a shared goal and which is appropriate in super-wicked problem contexts and that involves the creative use of different approaches for analysis. Since Soft OR, and its basis on collective decision-making, is essentially action oriented and located within a particular problem context and stakeholder grouping we can tolerate these new biases – should they be observed by an external observer conducting an ethnography (say) – more as features of the subsequent process-oriented analysis; there being no objectively defined rational basis available to the group to eliminate them or regard them as deleterious to the decision-making process.

References

Babai M Z, Ali M M and Nikolopoulos K (2012). Impact of Temporal Aggregation on Stock Control Performance of Intermittent Demand Estimators: Empirical Analysis. *Omega* **40**: 713-721.

Baron R A and Ensley M D (2006). Opportunity Recognition as the Detection of Meaningful patterns: Evidence from Comparisons of Novice and Experienced Entrepreneurs. *Management Science* **52**: 1331-1344.

Bentley R A, O'Brien M J and Brock W A (2014). Mapping Collective Behaviour in the Big-Data Era. *Behavioural and Brain Sciences* **37**: 63-76.

Brabham D C (2009). Crowdsourcing the Public Participation Process for Planning Projects. *Planning Theory* **8**: 242–262.

Brown P and Lauder H (2012). The Great Transformation in the Global Labour Market. *Soundings*, **51**: 41-53.

Chen H, Chiang R and Storey V (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly* **36**:1165–88.

Chen C P and Zhang C Y (2014). Data-Intensive Applications, Challenges, Techniques and Technologies: A survey on Big Data. *Information Sciences* **275**: 314-347.

Davenport T and Harris J (2007). *Competing on Analytics: The New Science of Winning*. Harvard Business School Press.

Davenport T, Harris J and Morison R (2010). *Analytics at Work: Smarter Decisions, Better Results*. Harvard Business School Press.

Eppler M J and Mengis J (2004). The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS and Related Disciplines. *The Information Society* **20**: 325-344.

Frisch D and Baron J (1988). Ambiguity and Rationality. *Journal of Behavioral Decision Making* **1**: 149–157.

Giguère G and Love B C (2013). Limits in Decision Making arise from Limits in Memory Retrieval. *Proceedings of the National Academy of Sciences USA* **110**:7613–7618.

Gilovich T, Griffin D W and Kahneman, D (2002). *Heuristics and Biases: The Psychology of Intuitive Judgement*. Cambridge University Press, Cambridge.

Goel S, Hofman J M, Lahaie S, Pennock D M and Watts D J (2010). Predicting Consumer Behaviour with Web Search. *Proceedings of the National Academy of Sciences USA* **107**: 17486-17490.

Gurstein M B (2011). Open Data: Empowering the Empowered or Effective Data Use for Everyone? *First Monday* **16**.

Hilbert M (2012). Toward a Synthesis of Cognitive Biases: How Noisy Information Processing can Bias Human Decision Making. *Psychological Bulletin* **138**: 211-237.

Jacoby J (1977). Information Load and Decision Quality: Some Contested Issues. *Journal of Marketing Research* **14**: 569-573.

Kahneman, D and Tversky A (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica: Journal of the Econometric Society* **47**(2) 263291.

Kahneman D, Slovic P and Tversky A (1982). *Judgment under Uncertainty: Heuristics and Biases*. Cambridge University Press.

King G (2011). Ensuring the Data-rich Future of the Social Sciences. *Science* **331**:719.

Liberatore M and Luo W (2010). The Analytics Movement: Implications for Operations Research. *Interfaces* **40**: 313-336.

McAfee A and Brynjolfsson E (2012). Big Data: The Management Revolution. *Harvard Business Review* **90**: 60-68.

Mingers J and Rosenhead J (2004). Problem Structuring Methods in Action. *European Journal of Operational Research* **152**: 530-554.

Moat H S, Curme C, Stanley H E and Preis T (2014). Anticipating Stock Market Movements with Google and Wikipedia. In: Matrasulov D and Stanley H E (eds). *Nonlinear Phenomena in Complex Systems: From Nano to Macro Scale* (pp. 47-59). Springer: Netherlands.

Ormerod R J and Ulrich W (2013). Operational Research and Ethics: A Literature Review. *European Journal of Operational Research* ***228***: 291-307.

Pfister H R and Böhm G (2008). The Multiplicity of Emotions: A Framework of Emotional Functions in Decision Making. *Judgment and Decision Making* **3**: 5-17.

Ranyard J C, Fildes R and Hu T I (2015). Reassessing the Scope of OR Practice: The Influences of Problem Structuring Methods and the Analytics Movement. *European Journal of Operational Research* **245**: 1-13.

Schintler L and Kulkani K (2014). Big Data for Policy Analysis: The Good, The Bad and The Ugly. *Review of Policy Research* **31**: 343-348.

Schroder H M, Driver M J and Streufert S (1967). *Human Information Processing*. New York: Holt, Rinehart & Winston.

Sen A (2013). A Comparison of Mixed and Dynamic Pricing Policies in Revenue Management. *Omega* **41**: 586-597.

Simchi-Levi D (2014). OM Forum-OM Research: From Problem-Driven to Data-Driven Research. *Manufacturing & Service Operations Management* **16**: 210.

Simon H A (1955). A Behavioural Model of Rational Choice. *Quarterly Journal of Economics* **69**: 99-118.

Singhal K and Singhal J (2012). Imperatives of the Science of Operations and Supply-Chain Management. *Journal of Operations Management* **30**: 237-244.

Surowiecki J (2004). *The Wisdom of Crowds: Why the Many are Smarter than the Few*. London: Little, Brown

Van de Ven, A. H., & Poole, M. S. (2005). Alternative Approaches for Studying Organizational Change. *Organization Studies* **26**: 1377-1404.

White L (2016). Behavioural Operational Research: Towards a Framework for Understanding Behaviour in or Interventions. *European Journal of Operational Research*. **249**(3), 827-841.