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Sheng, Jie and Amankwah-Amoah, Joseph and Khan, Zaheer and Wang, Xiaojun (2020) COVID-19 Pandemic in the New Era of Big Data Analytics: Methodological Innovations and Future Research Directions. *British Journal of Management*. ISSN 1045-3172.

DOI

<https://doi.org/10.1111/1467-8551.12441>

Link to record in KAR

<https://kar.kent.ac.uk/83010/>

Document Version

Author's Accepted Manuscript

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COVID-19 Pandemic in the New Era of Big Data Analytics: Methodological Innovations and Future Research Directions

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Although scholars in management recognize the value of harnessing big data to understand, predict and respond to future events, there remains little or very limited overview of how various analytics techniques can be harnessed to provide the basis for guiding scholars in studying contemporary management topics and global grand challenges raised by the COVID-19 pandemic. In this *Methodology Corner*, we present a review of the methodological innovations in studying big data analytics and how they can be better utilized to examine contemporary organizational issues. We provide insights on methods in descriptive/diagnostic, predictive and prescriptive analytics, and how they can be leveraged to study 'black swan' events such as the COVID-19-related global crisis and its aftermath's implications for managers and policymakers.

Introduction

The spread of the COVID-19 global pandemic has generated an exponentially mounting and extraordinary volume of data that can be harnessed to improve our understanding of big data management research as well as exemplifying the necessity among scholars, practitioners and policymakers for a better and deeper understanding of a range of analytical tools that could be utilized to better anticipate and respond to such unforeseen 'black swan' events and risks (see Ienca and Vayena, 2020; Wang, Ng and Brook, 2020; World Health Organisation, 2020a). In the face of COVID-19, which has led to more than 26 million cases and over 800,000 fatalities, impacting over 200 nations at the time of writing (Worldometers, 2020), many governments have been forced to forge a closer relationship with science and lean towards data-driven decisions for effectively responding to the unprecedented challenges caused by COVID-19.

Indeed, advancements and proliferation of different technologies have culminated in unprecedented production of mobile, digital devices and a vast amount of structured and unstructured data to be mined by firms and governments for sound and timely decision-making (Han, Park and Oh, 2016; Wedel and Kannan, 2016; Wu, Hitt and Lou, 2020). For instance, Henke, Puri and Saleh (2020) indicate that 'organisations are standing up analytics capabilities in a matter of weeks to inform business responses to COVID-19 challenges and prepare for the future'. Henke, Puri and Saleh (2020), in a McKinsey's report, suggest that such data analytics capabilities could offer between \$9.5 trillion and \$15.4 trillion in annual economic value to organizations. These trends show that big data analytics potentially offers important insights to managers and policymakers alike. From the 1800s to modern times, the time for new technologies to diffuse has shrunk from around 100 years to within a decade for multiple technologies (Comin and

Hobijn, 2004; World Bank, 2008), thereby ushering in a new environment where access to technologies, information and data has become increasingly common across the globe.

Although there has been amassing of both unstructured and semi-structured data across the globe on such exogenous shocks (Dai *et al.*, 2019), much of the current growing data remains untapped, to the detriment of wider society and policy. As recently observed by The Economist (2017), ‘the world’s most valuable resource is no longer oil, but data’ (p. 7). The issue of the world’s underutilized asset is exacerbated by a growing number of methodological approaches, but we lack a deeper understanding of the different techniques and how some can be utilized in concert to improve researchers’ approaches and tackle new global issues such as COVID-19. Indeed, data-driven decisions and analytics capabilities are particularly valuable to organizations in terms of fostering process innovation (Wu, Hitt and Lou, 2020; Wu, Lou and Hitt, 2019), supply chain design management (e.g. Waller and Fawcett, 2013), knowledge management (Khan and Vorley, 2017) and quality of decision-making (cf. Shamim *et al.*, 2019). Harnessing the potential of big data analytics is crucial for firms to mitigate the impact of global crises, like the scale of COVID-19. COVID-19 has prompted organizations to turn to real-time analytics tools and seek dependable and reliable information to better understand the effects on their activities (Kent, 2020). By mobilizing and analysing the data around exogenous events such as COVID-19, governments and firms would be better able to design their services, directives and guidelines, which ultimately lead to more well-grounded decisions. Among the benefits, analytic models provide an opportunity to explore ‘worst-case, best-case and most-likely scenarios’ (Kent, 2020, n.p.).

Given the extremely rare – and difficult to predict – adverse effects on national economies and businesses, the COVID-19 pandemic can be construed as a ‘black swan’ event (Yarovaya, Matkovskyy and Jalan, 2020). Firms can use big data analytic techniques to deal with extreme uncertainties such as those caused by the current COVID-19 pandemic. For instance, firms are using big data analytics to manage and mitigate uncertainties and bottlenecks in supply chains. It is in such a context that the current crisis not only demands a review of the existing range of meth-

ods and approaches, but also how best to pursue innovation in methodology to foster a better understanding of new global challenges. Against this backdrop, the purpose of this paper is to review the literature on descriptive and diagnostic, predictive and prescriptive analytics for big data to outline how they can be harnessed in studying these emerging challenges.

Theoretically, our study contributes to big data analytics research (Amankwah-Amoah and Adomako, 2019; Khan and Vorley, 2017; Sena *et al.*, 2019; Sheng, Amankwah-Amoah and Wang, 2017, Sheng, Amankwah-Amoah, Wang and Khan, 2019) and the ongoing discourse on COVID-19 in management research (cf. Amankwah-Amoah, 2020; Beech and Anseel, 2020; Budhwar and Cumming, 2020; Verbeke, 2020) by highlighting the range of existing big data analytics techniques and how they can be mobilized to improve scholarly understanding and inform managerial and public policy around global pandemics. In addition, beyond providing a comprehensive review of the literature on big data analytics, we outline how these can be leveraged in addressing contemporary management issues stemming from COVID-19 and beyond.

The rest of the paper is structured as follows. First, we introduce our approach to the review of the literature and outline different analytics methods in use. We then highlight some recent analytics studies by management scholars. Based on our assessment of various approaches and techniques, we outline methodological innovations and propose new ways of advancing analytics and studying current global crises such as COVID-19 in the context of big data.

Big data analytics: Methods in use

In this section, we survey popular techniques of big data analytics used in the business management disciplines. To that end, we collected empirical and analytical articles that performed big data analytics techniques. The survey of literature followed the general guidelines for a scoping review (Arksey and O’Malley, 2005). We used EBSCOhost Business Source Complete as the main database to commence the literature search, zooming in on academic articles that were written in English and published in management journals from 2011 to July 2020.

In generating a preliminary list of studies, a range of relevant terms and keywords were searched for in the title, abstract and keywords of articles. The relevant terms used in the search included ‘big data research’, ‘big data analytics/analysis’, ‘big data methodology(ies)/method(s)’, ‘big data technique(s)’, ‘descriptive/diagnostic analytics’, ‘predictive analytics/analysis’ and ‘prescriptive analytics/analysis’. We restricted our search list to the business and management top-ranked journals listed in the Academic Journal Guide 2018.¹ The initial search yielded over 170 results. The selection process started with reading the abstract to ensure the research topic centres around analytics. Next, the entire article was screened to understand the research aim and design. About 50 articles are conceptual pieces that present a theoretical lens of how organizations should develop big data analytics capabilities to create competitive advantages in a general sense. These articles were excluded from our analysis because they provide little information on the technical frontier. The remaining outputs are all empirical studies. Each article was carefully read to ensure the selected studies focus on analysing big datasets with an application of one or multiple analytics techniques. We thus removed articles that aim to develop architecture or improve the framework of data acquisition, storage and processing without explicit business implementation. The final sample covers 82 articles published over the past decade.

In reviewing each article, key information about the methodology and application areas was recorded. Theoretical development in research on big data analytics has strived to incorporate several perspectives to synthesize the existing body of knowledge and set the agenda for future research. In light of the main focus of the current study, which is to compile a list of data analytics methods for firms and researchers to reflect on how to strategize data in business responses to – and recovery after – the pandemic, we draw on the taxonomy of analytics developed in the current literature, including descriptive, predictive and prescriptive analytics (Wang *et al.*, 2016), to summarize the methods in use. Following that, we discuss a few methodological trends that emerged from the findings of our survey.

¹<https://chartereddabs.org/academic-journal-guide-2018/>.

Descriptive and diagnostic analytics

Taking on a retrospective view of what happened in the past, descriptive and diagnostic analytics present data in an understandable format and investigate the cause and effect relationships. Descriptive data analysis summarizes past data to provide an overview of potential patterns or trends embedded in data, which is also known as business reporting (Delen and Demirkan, 2013). A static report relies on statistical calculations of historical data to identify the distributions over a sample or a population. A dynamic view of business performance uses a wide range of visualization techniques – such as a dashboard with a graphical interface or an interactive graph, which informs decision-makers about the current situation in a timely and continuous way. Going beyond a surface examination, diagnostic analytics provides an historical account, from which problems and opportunities within existing operations can be identified. Causal-explanatory statistical modelling is the normal approach employed. Relying on statistical inference, researchers test theoretical reasoning-supported hypotheses and assess the explanatory power of the causal models.

Predictive analytics

Predictive analytics concerns what will happen in the future and is generally considered as the use of ‘statistical techniques to analyse current and historical facts to make predictions about future events and/or behaviour’ (Lehrer *et al.*, 2018, p. 429). A broader conceptualization suggests that ‘predictive analytics include empirical methods (statistical and other) that generate data predictions as well as methods for assessing predictive power’ (Shmueli and Koppius, 2011, p. 553). We classify predictive analytics techniques into three categories: statistical inference, machine learning and methods for analysing unstructured data. Table 1 shows the main methods utilized in predictive analytics.

This review demonstrates that the conventional methods in the context of big data highlight the capability of statistical and econometrics modelling in dealing with extremely large and high-dimensional structured data. Research in this line explores the plausibility of statistical approaches in the context of predictive modelling on big data, such as structural equation models (e.g. Evermann

Table 1. Main methods in predictive analytics

Methods categories	Brief description	Applications	Example references
Statistical inference	Use statistical approach to analyse a large amount and high-dimensional structured dataset.	Resource allocation; risk evaluation; churn prediction.	Evermann and Tate (2016), Moeyersoms and Martens (2015), Pérez-Martin, Pérez-Torregrosa and Vaca (2018), Saboo, Kumar and Park (2016)
Machine learning	Regression, neural network, classification, clustering, association, deep learning	Capacity planning; risk profiling; customer segmentation; demand forecasting; sales forecasting; churn prediction; fault detection.	Araz, Olsson and Ramirez-Nafarrate (2019), Ballings and Van Den Poel (2015), Bardhan <i>et al.</i> (2015), Bokelmann and Lessmann (2019), Boone <i>et al.</i> (2019), Coussement, Lessmann and Verstraeten (2017), De Caigny, Coussement and De Bock (2018), Kim and Pant (2019), Kumar <i>et al.</i> (2016, 2019), Kuzey, Uyar and Delen (2014), Lau, Zhang and Xu (2018), Li <i>et al.</i> (2017), Lin <i>et al.</i> (2017), Liu and Tseng (2018), Pérez-Martin, Pérez-Torregrosa and Vaca (2018), Sun <i>et al.</i> (2019), Zolbanin and Delen (2018)
Methods for unstructured data analysis	Text mining, image analysis, sentiment analysis, web mining, social network analysis, visualization	Predict customer or user behaviour; recommendation; monitor product or service quality; real-time reaction.	Abbasi <i>et al.</i> (2015), Appel <i>et al.</i> (2014), Bigsby, Ohlmann and Zhao (2019), Chae (2015), Feuerriegel and Gordon (2018), Gerber (2014), Han, Park and Oh (2016), He, Liu and Xiong (2016), Kauffmann <i>et al.</i> (2019), Kim, Kim and Park (2017), Liu <i>et al.</i> (2019), Liu (2020), Ma <i>et al.</i> (2019), Miah <i>et al.</i> (2017), Micu <i>et al.</i> (2017), Mukherjee and Sinha (2018), Pourmarakis, Sotiropoulos and Giaglis (2017), Salehan and Kim (2016), Shi, Lee and Whinston (2016), Singh, Shukla and Mishra (2018), Sun <i>et al.</i> (2015), van der Spoel, Amrit and van Hillegersberg (2017), Wasesa, Stam and van Heck (2017), Zhou <i>et al.</i> (2016)

and Tate, 2016), multilevel linear regression (e.g. Saboo, Kumar and Park, 2016), linear mixed models (e.g. Pérez-Martín, Pérez-Torregrosa and Vaca, 2018) and logit regression (e.g. Moeyersoms and Martens, 2015), among others. These multivariate approaches are refined to address issues like endogeneity, heterogeneity and autocorrelation (Saboo, Kumar and Park, 2016). With the inclusion of a large volume of information generated from diverse sources in real time, conventional methods uplifted to a big data level have demonstrated the statistical and predictive power required to understand a phenomenon more comprehensively.

While statistical methods can still be useful for medium to large-sized data, they rely on well-defined questions and models to make inference and prediction. It appears inadequate for analysing very large datasets and diverse types of structured and unstructured data where an 'algorithmic approach' (Tonidandel, King and Cortina, 2018, p. 527) is required. Algorithmic approaches emphasize the exploratory and data-driven process of generating and validating a predictive model. The core of the algorithmic approaches is machine learning, which generally subdivides into supervised, unsupervised and semi-supervised learning models (Sivarajah *et al.*, 2017). In the management field, supervised learning is often used to predict future outcomes formed on regression and classification (Grover *et al.*, 2018). Management researchers have exploited algorithms to solve a wide range of business problems (see Table 1). In particular, machine learning and neural networks are often employed in forecasting demand and sales, and the forecasting accuracy is expected to be improved with the use of analytics due to the enriched pool of historical and current data.

In addition, analysing both structured and unstructured data becomes an important source for understanding patterns in data. For example, natural language datasets present extraordinary versatility. User-generated content is frequently analysed to understand and predict customer behaviour. Coupled with unsupervised learning methods such as clustering and dimension reduction, an analysis of the semantically coherent groups and themes emerging from textual corpus or images is found to be helpful to assist operational decisions (see example studies in Table 1). In addition to textual data, other types of unstructured data, such as GPS and satellite-based tracking data, social networks, mobile app and web us-

age data, also presented significant value in evaluating and improving business practices. The unstructured data introduces generous information by extracting knowledge from which we can create informed and proactive interventions. Readers can refer to Balducci and Marinova (2018) for a comprehensive list of computational methods in marketing research, which is also useful and can be applied in many other management fields.

Prescriptive analytics

Addressing questions like 'what should I do' and 'why should I do it', prescriptive analytics is less exposed as compared to the descriptive and predictive analytics discussed in the previous sections. Sivarajah *et al.* (2017) argue that prescriptive solutions determine actions and evaluate their impact on business objectives, requirements and constraints and, in doing so, support business analysts in making decisions. Prescriptive analytics has recently attracted increasing research interest and been considered as the next step towards the development of business analytics, resulting in optimized decision-making for business performance improvement (Larson and Chang, 2016; Lepenioti *et al.*, 2020). Šikšnys and Pedersen (2016) consider prescriptive analytics as the most sophisticated type of business analytics, that is capable of generating the greatest intelligence and value for businesses. In the systematic literature review of prescriptive analytics, Lepenioti *et al.* (2020) conclude that as a critical advancement in analytics, prescriptive analytics can improve decision-making and process effectiveness. Through reviewing the relevant articles on prescriptive analytics, we classify the prescriptive analytics methods into four main categories: mathematical programming, simulation, evolutionary computation and logic-based models, as illustrated in Table 2.

Most of the articles on prescriptive analytics concentrate on optimization methods and algorithms. Among them, linear programming and its extensions (e.g. mixed integer linear programming and binary linear programming) are most frequently used. Due to the uncertain nature of many problems, stochastic optimization is deployed when an objective function contains random elements. There is also increasing use of Bayesian optimization, a technique for efficiently optimizing complex objective functions with computationally expensive function evaluations

Table 2. Main methods in prescriptive analytics

Methods categories	Brief description	Applications	Example references
Optimization	<p>Linear programming and its extensions</p> <p>A technique of optimizing a linear objective function. Its extensions include mixed integer programming (i.e. variables are integers) and binary/linear programming (i.e. variables are binary).</p> <p>Nonlinear programming</p> <p>A technique of solving an optimization problem when the objective function or some of the constraints is/are nonlinear.</p> <p>Stochastic optimization</p> <p>A collection of the optimization methods when an objective function contains random elements (e.g. demand and supply).</p> <p>Bayesian optimization</p> <p>A technique of optimizing objective functions that are complex and/or expensive to evaluate.</p> <p>Evolutionary computation</p> <p>Biological evolution-inspired algorithms for global optimization.</p>	<p>Brochure pricing; marketing intervention; capacity planning.</p> <p>Asset management; pricing strategy.</p> <p>Human resource management; inventory management.</p> <p>Public health; credit collections.</p> <p>Resource allocation and scheduling; project contract design.</p> <p>Smart manufacturing systems; healthcare management; developing strategic maps for the PC industry.</p> <p>Localizing underwater robots; smart city; manufacturing maintenance planning.</p>	<p>Baur, Klein and Steinhardt (2014), Ghoniem <i>et al.</i> (2017), Lo and Pachamanova (2015)</p> <p>Goyal <i>et al.</i> (2016), Ito and Fujimaki (2017)</p> <p>Berk <i>et al.</i> (2019), Bertsimas and Kallus (2019)</p> <p>Chehrizi, Glynn and Weber (2019), Harikumar <i>et al.</i> (2018)</p> <p>Kerkhove and Vanhoucke (2017), Xiong <i>et al.</i> (2016)</p> <p>Jain, Shao and Shin (2017), Srinivas and Ravindran (2018), Wang, Cheng and Deng (2018)</p> <p>Costa <i>et al.</i> (2017), Kreinovich and Ouncharoen (2015), Matyas <i>et al.</i> (2017)</p>
Simulation	<p>A technique of modelling a real-life or hypothetical operation/system to predict the behaviour of the system and facilitate decision-making.</p>		
Logic-based models	<p>A hypothesized representation of theory of change about how an intervention leads to an outcome of interest.</p>		

(Lepenioti *et al.*, 2020). Evolutionary computation, biological evolution-inspired algorithms for global optimization (Bäck, Fogel and Michalewicz, 1997), are used to provide approximate solutions when problems become too complex to get optimal solutions with the above-mentioned optimization methods. Simulation is often utilized in prescriptive analytics with the purpose of improving the effectiveness of decision-making of humans or decision logic embedded in applications (Lepenioti *et al.*, 2020). Simulation is particularly useful to test new ideas about business and management decisions as it can illustrate the eventual effects of different conditions and alterations on an existing process or system. Logic-based models are often used in prescriptive analytics applications for supporting proactive decision-making on the basis of domain expert knowledge. Nevertheless, with the increasing availability of data for model development, Lepenioti *et al.* (2020) call for prescriptive analytics models to be less dependent on domain expert knowledge and more dependent on data-driven approaches such as data mining and machine learning methods.

Current methodological trends

By reviewing the techniques adopted in the recent big data studies, we observe a few methodological trends in the development of business and management research in this field.

Diversified data in place. Big data is characterized by high volume, velocity, variety and complexity. Nevertheless, the benefits of big data analytics appear not to be derived from the enormous size of the data, but only emerge when working with fine-grained data (Bradlow *et al.*, 2017; Martens *et al.*, 2016). It is observed that many studies combine various sources of data that enable a 360-degree view of the study object. This may include large structured datasets and various types of unstructured data such as text, newsfeeds, tweets, social bots, social media and web data. Data diversification requires a hybrid of two or more methods to process and analyse data. A typical example is to use machine learning approaches to quantify unstructured data and include them as inputs into statistical models to offer computational solutions. These data sources are complementary in relation to improving predictive performance.

Meanwhile, considering the variability and complexity of big data, studies in this area tend to compare the results of several algorithms or combine a few algorithms to optimize the predictive power. But choosing the best-performing algorithm is not straightforward. No one algorithm could possibly fit the data better in all cases, and scholars have suggested selecting the model offering ‘the best balance between bias and variance’ (Diana, 2018, p. 149).

Mixed types of analytics. Due to the complexity of the studied problems and the above-mentioned data diversity, big data research often adopts a mixed-methods approach that combines various analytics to analyse multi-structured (structured and unstructured) and multi-sourced data (Wedel and Kannan, 2016). Predictive analytics is often built based on insights from descriptive analytics, such as performing and presenting social network analysis with data visualization (Chang, 2018) and developing a visual analytics and reporting system for supply chain management (Park, Bellamy and Basole, 2016). Predictive analytics can be incorporated in the prescriptive analytics applications so as to enable organizations to improve optimization models based on feedback received from data-driven predictive analytics models (e.g. Bertsimas and Kallus, 2019; Huang, Bergman and Gopal, 2019; Srinivas and Ravindran, 2018; Zhi, Wang and Xu, 2020). Indeed, prescriptive analytics – in conjunction with descriptive and predictive analytics approaches such as data mining, machine learning and data visualization – is proven to substantially improve the efficiency and effectiveness of analytics by feeding data-driven inputs forward to parameterize and build prescriptive models, as well as feeding synthetic data back to tune predictive algorithms (Greasley and Edwards, 2019).

Technological frontier. While the majority of reviewed studies employ the aforementioned analytical approaches, recent breakthroughs in computer science have received increased attention of management scholars. Advanced technologies, such as artificial intelligence (AI) and robotics, have been brought to the forefront of discussions. AI often appears together with the underlying machine learning algorithms, such as artificial neural networks (ANNs), employed to fully automate data processing and model building (e.g. Kim, Park and Suh, 2020; Lee *et al.*, 2020; Pitt, Bal and Plangger, 2020). Compared to conventional machine

learning algorithms, deep learning algorithms – such as convolutional neural networks (CNNs) or recursive neural networks (RNNs) – are gaining popularity, with superior performance (Fang *et al.*, 2020). Despite the substantial benefits of AI and embedded algorithms, a number of studies imply that the key for success is human–computer collaboration instead of relying on the intelligence of one party (Liu *et al.*, 2019; Yan *et al.*, 2017). Moving forward, the black box of AI and deep learning needs to be unmasked with explainable AI (XAI) techniques to achieve both prediction accuracy and explainability (Rai, 2020).

Harnessing analytics to tackle some of the contemporary mainstream management research agenda/challenges and COVID-19 related issues

Principally dominated by epidemiological models, national governments and healthcare authorities have relied on modelling expertise extensively to make important decisions in combating coronavirus outbreaks and mitigating the economic and social effects on different communities. Given the unparalleled shock triggered by COVID-19, hard to predict as a ‘black swan event’ (Yarovaya, Matkovskyy and Jalan, 2020), there is a need for better understanding of analytics techniques to help organizational leaders and managers better identify looming challenges and make sense of their environments and make data-driven quality decisions. Such methods can help businesses to cope with extreme uncertainties and unpredictable events. For example, firms can utilize big data analytic methods to make effective decisions about uncertain events such as selecting a particular market for investment, predicting potential risks and growth in their respective sectors, identifying potential alliance partners and suppliers, or developing new products and services for customers. In addition, big data analytic methods can enable businesses to deal with uncertainties associated with the black swan event, such as the wellbeing of their employees, making sound financial decisions and effectively and efficiently managing supply chain safety and other extreme external political, legal, economic and social risks (cf. Henke, Puri and Saleh, 2020). Black swan events such as those caused by COVID-19 can also amplify business

failures (Amankwah-Amoah, Khan and Wood, 2020), and firms could utilize big data analytics methods to mitigate external risks and reduce business failures through sound business planning and forecasting. Therefore, from emergency hospital operations management to supply chain resilience development, different analytics approaches can play an important role in the immediate response to the COVID-19 pandemic and the economic recovery after the pandemic. Drawing insights from the review of the different analytics techniques – including descriptive, predictive and prescriptive analytics – provides an opportunity to outline how they can be harnessed to study some of the contemporary management topics and COVID-19 issues, including: the future of work (human resources and organizational behaviour-related challenges), new marketing practices with changing consumer behaviour, product/service development and innovation, global value chains, challenges in sustainability, governance and public policy as demonstrated in Table 3. We set out future directions for management scholars to explore how to employ data analytics to help businesses respond to – and recover from – the global crisis caused by the COVID-19 pandemic.

Future of work

The first area of our focus here relates to what we broadly view as ‘future of work’ (human resources and organizational behaviour-related challenges) issues. The dynamic changes in the global economy – some precipitated by pandemics and other by technological development – have led to the destruction of jobs. There is a need to examine these megatrends and their effects on the labour market. As demonstrated in Table 3, there are a number of promising questions that can be pursued utilizing the techniques noted. From a strategic human resources perspective, organizational leaders will be able to predict the performance of individual employees and teams via mining internal digital existence such as emails, chats and employee-generated content, combined with data from human resources information systems and performance management systems (Leonardi and Contractor, 2018). Besides, insights from the review suggested that analytics has the potential to provide a deeper understanding of work arrangements, work design and routines. In the COVID-19 pandemic, homeworking has become a new norm

Table 3. Leveraging data analytics techniques to study major themes in management

Key themes in management	Description	What we need to know: some questions for future research	Methods categories: how analytics can inform understanding
Future of work (human resources – challenges) – critical and less critical work	Assessing the impact of new technologies, social-economic conditions and health care issues in redesigning and embracing new work practices. Also, situated within the nexus of the impact of technology via digitalization and wider applications and utilizations of AI to influence work and how it can be undertaken.	To what extent and in what ways can business analytics be harnessed to improve work conditions and design across developing and developed markets? How does COVID-19 influence predictive analytical tools that are utilized for distribution of work? How do organizations manage employees whilst fostering social interaction with ‘work from home’? How do firms best foster workers’ collaboration, virtual and in-person, while maintaining social distancing? How have new technologies impacted on the emotional wellbeing and resilience of workers? How does crisis foster green human resource practices?	Use ‘people analytics’ with descriptive and diagnostic approaches to understand employees’ needs and situation to stabilize current operations; use predictive analytics to plan for the return to the workplace, as well as employee wellbeing and resilience.
Consumer behaviour and new marketing practices	Changes in consumers’ buying patterns, including panic buying, hoarding and changing perceptions about different brands, with varying effects on brick-and-mortar and online outlets.	How to use consumer behaviour and/or attitudinal data collected in real time to adjust marketing scenario plans? What is the impact of branding, marketing, communications and social responsibility performed by businesses during the pandemic? What is the implication of analytics for strengthening customer relationships and engagement during and after the pandemic? How can analytics predict and prepare businesses for adapting to the new ‘norms’ in consumption and marketing practices? What is the role of AI and advanced technologies in developing agile marketing strategies and demand-driven business models?	Descriptive and diagnostic analytics to analyse real-time data to monitor the situation and identify changes in markets and consumer behaviour; predictive analytics to predict demand and future customer engagement behaviour.

Table 3. Continued

Key themes in management	Description	What we need to know: some questions for future research	Methods categories: how analytics can inform understanding
Product/service development and innovation	<p>Changing consumer demand for goods/services during and post-pandemic. An acceleration in adoption of technologies in product/service production and delivery.</p>	<p>How does the evolving consumer behaviour change the landscape of retailing and commerce? What is the role of technology in facilitating product development and innovation? How do organizations utilize prescriptive analytics to innovate and scale up their business model? What business model is more suitable for this post-crisis era?</p>	<p>Descriptive/diagnostic analytics to understand behavioural changes; predictive analytics (current and historical data) to make future predictions; prescriptive analytics to configure and test innovations.</p>
Global value chains and future resilience	<p>Global supply chains require re-evaluation and re-shaping. Greater transparency is needed for both upstream and downstream supply chains. Capability for fast response and agility is essential to enhance resilience.</p>	<p>What are the implications of COVID-19 for manufacturing and global supply chains? How to re-shape and re-orient global value chains to control costs, increase resilience and create value? Can substantive nationalization or regionalization of supply chains cope with future shocks better? How to use technologies to enhance the sustainability of supply chains? How do consumers react to announcements of firms' commitments to environmental sustainability issues during a crisis like COVID-19? Do consumers place greater importance on environmental sustainability issues post-crisis relative to during crisis? What has been the effect of COVID-19 on water and air pollution? How do governments better enact sustainability policies after a crisis?</p>	<p>Predictive analytics to support real-time demand sensing; prescriptive analytics to test supply chain innovation.</p>
Sustainability, governance, and public policy issues	<p>Focused on how governments perform their functions and their impact on society.</p>	<p>How do consumers react to announcements of firms' commitments to environmental sustainability issues during a crisis like COVID-19? Do consumers place greater importance on environmental sustainability issues post-crisis relative to during crisis? What has been the effect of COVID-19 on water and air pollution? How do governments better enact sustainability policies after a crisis?</p>	<p>Descriptive and diagnostic analytics to assess the impact of contingent policies; predictive analytics to estimate public perception and reaction to adjust policies.</p>

for many office workers. With this new norm of 'working from home', managing employees whilst fostering social interaction is a huge challenge for many organizations. 'People analytics' (Isson and Harriott, 2016; Leonardi and Contractor, 2018), with descriptive and diagnostic approaches, can be used to stabilize current operations by collecting and analysing data on employees' needs, home situations, workloads and additional stressors (Gray, 2020). Moving to the re-opening phase, predictive analytics can help predict the behavioural changes of employees caused by the COVID-19 crisis (de Haas *et al.*, 2020) and therefore plan for the return to the workplace. Merged with employees' personal information, a data pool of employees' health status, working conditions, performance, and so forth during quarantine across different departments and locations will provide an effective means to look at redesigning jobs towards embracing and monitoring home-based working, creating conditions for motivating the workforce and teams while maintaining social distancing, prioritizing positions to return to the office and identifying jobs to be eliminated, re-imagined or created. For example, Accenture launched an analytics-driven platform called 'People + Work Connect' that pools non-confidential and aggregated workforce information (e.g. location and experience) to help bring laid off or furloughed employees back to work quickly.

Changes in consumer behaviour and new marketing practices

Stemming from COVID-19, social distancing and quarantines have forced people to change their consumption behaviour. Such a crisis poses extreme uncertainties and a survival threat to brick-and-mortar businesses, and weakens their competitiveness (Amankwah-Amoah, 2018). Many retailers have experienced a sudden drop in sales for offline outlets, while demand for online groceries and quarantine essentials has hiked up by an unexpected amount. Due to the reduced traffic to physical stores, retailers who have the technological capability have learnt to improvise by transitioning to online product selling and delivery. These circumstances spark changes in consumer shopping habits, with customers self-serving or switching to services they are not used to patronizing. This change in consumer behaviour may be temporary, but it could be sustained even when the critical

stage of the crisis passes (Sheth, 2020). Moreover, consumers' perceptions and attitudes towards a brand or business may also change, depending on the actions taken by firms during this extreme period (He and Harris, 2020). For instance, consumers' awareness and opinions about a brand may be shaped or re-shaped by the social responsibility that business takes on (e.g. donating, producing hand sanitizer and face masks, supporting communities with an offer of empathy letters, giveaways, promotions, and so on).

The changes in consumer behaviour will require an adaptation of marketing practices to the current context, which also leads to new opportunities with the help of data analytics. In the middle of the crisis, it is important to collect data on a continuous basis in order to meet the evolving needs of consumers. On the one hand, the real-time data on sales, inventory, operations and market trends should be monitored to identify changes in the market through data mining and descriptive analytics. For example, Google launched a platform called Rising Retail Categories to help brands and manufacturers to track search interest across retail categories and locations. This enables firms to understand contemporary culture and develop a rapid response to an emergency (Swaminathan, 2018). On the other hand, scholars have suggested that brands should strengthen digital communications and interactions via online channels with customers during the emergency (Pantano *et al.*, 2020). It offers an opportunity to create an integrated data pool with abundant information, by soliciting which can provide a clear path moving forward. For instance, social media feeds help gauge customers' emotional reaction to brands and the multimedia content can be analysed with machine learning and AI to measure the effectiveness of marketing methods – such as advertisements and other brands' influencers in the lockdown (Taylor, 2020). Using machine learning and data mining techniques to analyse e-CRM captured data throughout the customer journey – such as customer preferences and purchasing habits revealed by web clickstream, online chats, web forums and so forth – is useful for firms to predict demand and manage customer relationships. An analytical upgrade can fundamentally improve marketing methods and innovation capabilities (Wang *et al.*, 2020) to be more agile in responding to the crisis, or when markets get back to 'normal'. Furthermore, in the longer term, we encourage

scholars to explore the adoption of AI and robotics solutions in developing marketing resilience, which appears to be an unexplored area (Grewal *et al.*, 2020). The use of new technologies in marketing can potentially enhance customer experiences by offering support to e-retailing, sales, customer service, and so on (Davenport *et al.*, 2020).

Product/service development and innovation

While many companies are struggling to survive during the COVID-19 pandemic, with customers under lockdown, shops shuttered and cash flow drying up, companies that sell essential items and basics (e.g. grocery stores) are doing well, especially those with a strong online presence. While service sectors including aviation, travel, entertainment, tourism and restaurants have been hit hardest as customers are more cautious about going out for leisure or entertainment, other businesses – such as delivery services, online entertainment, online shopping, online education and solutions for remote working – are thriving. It will take some time before businesses return to normality; and this ‘business normality’ may never be the same again considering the uncertainty of the COVID-19 pandemic, as millions of consumers are creating and reinforcing their online buying behaviours.

These behavioural changes are already moving towards completely changing the market landscape for years to come, which requires businesses to think hard and innovatively about their products/services as well as new ways of producing and delivering them during the pandemic and in the economic recovery when we come out of the pandemic. In this regard, prescriptive analytics enables businesses to reconfigure and test new innovations in products, service processes and business models. Besides, while big data-driven insights are helping epidemiologists, scientists and policymakers to comprehend and tackle the impacts of the COVID-19 pandemic, real-time internal and external data on customers’ purchasing records, employees’ information, operations’ transactional data and social media can also support firms to understand the change in consumer behaviour and the evolving market landscape. Rolls-Royce established a new alliance of data analytics that makes use of traditional economic, business, travel and retail datasets as well as behaviour and sentiment data, to provide new insights on the

impacts of COVID-19 and support businesses in the economic recovery. Descriptive and predictive analytics can help businesses to better understand consumer behavioural changes and foresee future demand for products/services. For instance, Hall *et al.* (2020) identify patterns of consumption displacement for the hospitality and retail sectors in the Canterbury region of New Zealand through analysing consumer spending data during the COVID-19 outbreak.

Operations and e-supply networks

COVID-19 has brought significant disruption to global supply chains from the critical movement of people, finished goods, raw materials to factory operations and supply chain partners’ operations. For instance, many businesses’ operations and staffing are dramatically altered because of social-distancing measures and the halt of major European automotive manufacturers’ production networks means the breakdown of the entire supply chains. Meanwhile, innovation and digital transformation will play an important role in economic recovery in the aftermath of the pandemic (Chesbrough, 2020; Hartmann and Lussier, 2020). For example, companies such as Amazon and Ocado that leverage advanced technologies such as robots and AI to manage their operations and supply chains have already proved to be winners during the COVID-19 pandemic (Kahn, 2020). Logistics service providers are able to overcome adverse conditions to provide essential supplies to hospitals and consumers with the support of digital technologies and Internet platforms. New models of workflow can be created with digital information and connectivity, transforming the traditional supply chains into e-supply networks, where organizations are connected with complete supply networks to enable end-to-end visibility, agility, collaboration and optimization (Dolgui, Ivanov and Sokolov, 2020; Ivanov, Dolgui and Sokolov, 2019).

While many companies are preoccupied with dealing with the immediate impact on their people, customers, suppliers and broader supply network partners, other organizations have gone further to restore supply chain operations and prepare for ‘the new normal’ regarding the manner in which supply and demand are matched. In recent times, real-time data (e.g. transactional data, sensor data, GPS data) are being constantly generated and collected along supply chains, big data

analytics approaches are also being used for critical operations, optimization and supply chain decisions in demand forecasting, supply and demand matching, allocation and rationing, transportation scheduling and last-minute delivery. For instance, to advance circularity in manufacturing, 3M applied sensors to existing equipment to monitor production and used data analytics in their Digital Factory programme to uncover waste and explore new efficiencies. Among the recent literature, Mehrotra *et al.* (2020) developed a stochastic optimization model for resource allocation and sharing with an application of ventilator allocation to fight COVID-19 and found that efficiency improvements can be achieved over time by establishing a central agency that acts as a coordinator to share critical resources that are in short supply. Choi (2020) developed mathematical optimization models to explore how logistics and technologies together can innovate 'Bring-Service-Near-Your-Home' operations under the COVID-19 pandemic. The analytical study examined the impacts of this mobile service operation on business and consumers and provides important guidance to practitioners and governments. Ivanov (2020a) presents a simulation study for observation and prediction of short-term and long-term impacts of epidemic outbreaks and uncovers some critical parameters and scenarios of positive and negative supply chain performance dynamics. While predictive analytics can support real-time demand sensing and optimization of supply chains to cut costs, prescriptive analytics can help companies to make informed decisions on innovative supply chain models that enable fast response in allocating and delivering the products required by customers in an efficient and timely manner. It is in such a context that Henke, Puri and Saleh (2020, p. 6) note the importance of analytics for supply chain fast response time and provide important insights on the use of analytics by an automotive parts supplier. They note that 'at one automotive-parts supplier, leaders could rapidly adjust production capacity after supply-chain, manufacturing, marketing, and analytics staff collaborated on a forecasting tool that anticipates sales by market and vehicle type across several dimensions, including the macroeconomic impact of COVID-19, consumer acceptance of new automotive technology and trends, and regulatory policies'. These trends reflect the enormous potential of big data analytics tools. Scholars can use both unstructured

data – such as newsfeeds, web forums, tweets, social media blogs and YouTube channels – and structured data in the form of survey responses of managers to predict the future resilience and long-term sustainability of supply chains.

Global value chains and future resilience

The prevailing economic motive behind the global value chains over the past decades is to pursue minimum overall costs and maximum efficiency, which has resulted in long and sophisticated global supply chains spread across the globe, but mainly concentrated in emerging and developing economies (Benito, Petersen and Welch, 2019; Gereffi and Lee, 2012). While recent political and economic events (e.g. the trade war between the USA and China, and Brexit) have underlined the trade fragility of global supply chains, the emergence of the COVID-19 pandemic is accelerating the change of global value delivery models. When the world recovers from the COVID-19 pandemic, the vulnerabilities and certain risks of the global supply chains can no longer be overlooked. The paradigm behind the global value chains will need to be re-evaluated and optimized. One possible outcome from such re-evaluation is that the long and sophisticated global supply chains will be reshaped and possibly shortened and, in some cases, may even become more regional and national (cf. Panwar, 2020; Rosa, Gugler and Verbeke, 2020). Other values – such as transparency, responsiveness, diversification and sustainability – will take a more prominent role to prevent future supply bottlenecks while enhancing supply chain resilience to future shocks.

Mitigating the impact of COVID-19 on the global value chains will require new approaches and tools for the aftermath re-evaluation, reshaping and governance of value chains (e.g. Verbeke, 2020). There is a great need for supply chain transparency, as businesses should have a good understanding of what is happening to their demand and supply in real time. While companies often use historical data for forecasting future demand and managing inventory, this can no longer serve its purpose in the changing and fast development of the COVID-19 pandemic. From the micro perspective, firms are collecting more real-time data than ever before from their internal operations, as well as from their supply chain partners. From the macro perspective, in addition

to the economic data from relevant governmental departments/offices, the Organisation for Economic Co-operation and Development² also provides raw trade-in value-added data to explore trade policy implications of global value chains. With the abundant data from various sources, big data analytics can play a key role in facilitating the re-evaluation, re-orienting and re-shaping of the global supply chains, thus minimizing risks and potential disruptions. Motivated by the COVID-19 outbreak, Ivanov and Dolgui (2020) propose a novel decision-making environment of the intertwined supply network (ISN) and viability, in which the viability formation is illustrated through dynamic game-theoretic modelling of a biological system that resembles the ISN. Ivanov (2020b) conceptualizes the notion of viable supply chain and demonstrates its value for decision-makers in designing a more resilient and sustainable supply chain through a system dynamics approach. Nevertheless, understanding the role of big data analytics in helping re-evaluate and restore the global value chains is a critical, but understudied, area of research, both from predictive and prescriptive perspectives.

Challenges in sustainability, governance and public policy

Historically, government departments and agencies have often lagged behind the private sector in terms of new technology adoption, utilization and innovation. Indeed, across the globe, government departments and agencies have often been found to rely mainly on obsolete technologies. The application of descriptive and predictive analytics and the timely update of COVID-19-related analytics results (i.e. rolling trend and 'R' rate) have helped many governments to develop public health policies and communicate effectively with the general public. Leveraging data analytics provides an opportunity to explore key issues such as the effects of national policies and current technologies used to enhance information flow, to provide information services in times of crisis such as COVID-19, and to foster quality and innovative government services in turbulent times. To advance research on predictive and prescriptive analytics, studies could

explore how government technological capabilities can be enhanced to identify and tackle the challenges emerging from COVID-19.

In light of the growing importance of environmental issues to governments and businesses, there is a need for an agenda to help bridge the gap between research and practice. Motivated by the need for better understanding of the sustainability agenda in the wake of the crisis, we suggest the need to leverage analytics to examine consumers' attitudes towards businesses during and after the crisis. In this direction, future studies could utilize descriptive and diagnostic analytics and predictive analytics of data such as carbon emissions, responsible consumption and production, policy intervention during the pandemic at country, regional and global level to examine whether crises such as this alter societal perception and attitudes towards environmental issues, how the changed behaviour generates positive or negative impacts on economic, environmental and social sustainability, and the best way to develop a resilient approach towards a sustainable recovery.

As demonstrated in the online Supplementary Appendix, we provide a number of cases illustrating how numerous firms have used analytics during the COVID-19 emergency to manage various business operations and challenges. In each case, we provide a brief description of the approaches to data analytic capabilities and discuss the nature of the use of analytics, its application and effects.

Conclusion

In conclusion, this *Methodology Corner* piece sought to present a review of the methodological innovations in studying big data analytics and how they can be utilized to examine contemporary organizational and management issues arising from the global pandemic caused by COVID-19, as well as other grand challenges of modern times. Given that COVID-19 is a 'black swan' event in that it is difficult to predict and assess its full effects (Yarovaya, Matkovskyy and Jalan, 2020), we contend that data analytics offers an effective pathway to better make sense of the event and how organizations can strategize and respond in this new era through the use of various big data analytic methods. In reviewing the extant literature on this topic, we provide important insights into the popular techniques adopted in the

²The Organisation for Economic Co-operation and Development, trade-in value-added data, <https://stats.oecd.org/index.aspx?queryid=75537>, accessed 28 July 2020.

descriptive/diagnostic, predictive and prescriptive analytics to address various business problems. Against the backdrop of the pandemic, our study outlines a number of challenges and big data analytics applications in areas such as the future of work, new marketing practices with changing consumer behaviours, product/service development and innovation, global value chains and challenges in sustainability, governance and public policies. With respect to these promising areas, we discuss a number of opportunities that will emerge for the management research community to use various analytical approaches to support the efforts made globally and locally to deal with the unprecedented challenges brought about by the COVID-19 pandemic and its aftermath, which will have long-term implications for the global economy. Data analytics offers important and significant opportunities for scholars across the developed and developing economies, interested in studying future employment trends, global crises and their impact on innovation and knowledge sharing, business resilience driven by the digital and analytics capabilities, and the future functioning and sustainability of global supply chains.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Supplementary Appendix: How Organizations Have Used Data Analytics During the COVID-19 Emergency