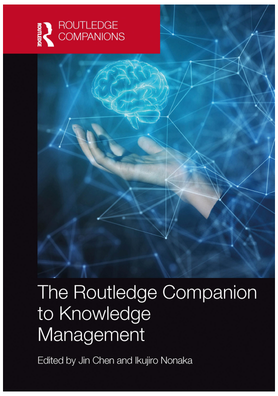

The Routledge Companion to Knowledge Management

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Demystifying the Link between Big Data and Knowledge Management for Organisational Decision-Making

Publication details
https://test.routledgehandbooks.com/doi/10.4324/9781003112150-11
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Published online on: 23 May 2022

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DEMYSTIFYING THE LINK BETWEEN BIG DATA AND KNOWLEDGE MANAGEMENT FOR ORGANISATIONAL DECISION-MAKING

Krishna Venkitachalam and Rachelle Bosua

Introduction

The knowledge management (KM) discipline has matured significantly over the past 30 years. Evidence of this comprises a variety of models, typologies and perspectives of knowledge, i.e. tacit versus explicit and objectivist versus practice-based knowledge (Jasimuddin, Klein and Connell, 2005; Hislop et al., 2018; Marabelli and Newell, 2014), the nature of knowledge, i.e. embrained, embodied, embedded, encoded and encultured (Blackler, 1995), knowledge creation, i.e. the SECI model (Nonaka, 1991a, 1991b; Nonaka and Hirose, 2015; Nonaka and Toyama, 2005; Nonaka and Toyama, 2003), knowledge strategy (Bosua and Venkitachalam, 2013; Hansen, Nohria and Tierney, 1999), dynamics in strategic KM (Venkitachalam and Willmott, 2015), strategic shifts in knowledge (Venkitachalam and Willmott, 2016), social perspectives on networking and the flow and use of knowledge in teams, social networks and across cultures (Adler and Kwon, 2002; Bosua and Scheepers, 2007; Cross et al., 2001; Nahapiet and Ghoshal, 1998).

In contrast, the fields of big data and business analytics[1] (BA) have emerged introducing analytics as a process of developing actionable decision-making or recommendations for actions using insights gathered from historical sets of data (Chen et al., 2012; Sharda et al., 2018). Hence, in the past decade, there has been significant growth and interest in big data. The increased focus on data as an important organisational resource is not new, as data has always been the backbone of traditional business processing applications and systems since the 70s. With the introduction of Web 2.0 and Hadoop in 2005, new developments in technology (e.g. digital platforms, cloud computing, AI and machine learning) accompanying tools to collect and process large volumes of structured and unstructured data resulted in a new era of 'datafication'. Datafication is described as a technology trend whereby every possible aspect of business and human life is changed into a digital form for the sake of adding value (Lycett, 2013; Sadowski, 2019).

From a computational perspective, the focus in recent years on big data and BA (Chen and Zhang, 2016; Lycett, 2013) has sparked a growing need to analyse data to gain a deeper understanding of business needs, trends and customer requirements. Over the past two decades

 DOI: 10.4324/9781003112150-11

the new discipline 'data science' has developed significantly to complement big data processing and make sense of datafication (Lycett, 2013; Stodden, 2020). As an evolving and interdisciplinary field, data science draws on computational methods, processes, statistical algorithms, data mining techniques, machine learning and IT platforms and systems to extract 'knowledge' and insights from large sets of structured and unstructured data. Predictions are that the future of digital business will significantly draw on data science to support BA, which may provide unlimited possibilities to create business value (Gartner, 2020; Hernán et al., 2019; Vicario and Coleman, 2020).

A review of the KM literature indicates that knowledge will remain to be one of the most important resources of the 21st century (Litvaj and Stancekova, 2015; Razzaq et al., 2019). In a recent global study by Heisig et al. (2016), the authors highlight the future research areas of KM influencing many organisational aspects including knowledge creation and sharing, innovation, knowledge worker productivity and performance, decision-making and competitive advantage. One area that is of specific importance is decision-making and KM. Since KM has a unique interdisciplinary nature, there is yet a scant understanding of how organisational decision-making in the context of KM is enabled by datafication. Since datafication features strongly in a competitive landscape, there is no clear link between the fields of big data and KM yet. Therefore, the aim of this chapter is to explore this link through the literature to determine how the two areas of big data and KM in organisations for decision-making can be bridged. Hence, the research question: *What is the bridging link between big data and KM for organisational decision-making?*

In unpacking this question, we focus on insights and prior literature on big data and KM with a focus on organisational decision-making. As part of the study insight/s, we introduce the idea of *'contextual knowledge experts'* and define these *'as humans who are equipped with a specific context (dependent or bounded) of know-what and know-how, and whose collective expertise is critical to decision-making needed in different facets of an organisation'.*

This chapter is structured as follows: the next section describes the approach followed to analyse the literature. Section 'Literature Background' highlights key themes that emerged from insights based on literature review in the areas of big data and KM in organisational decision-making. 'Conceptual Model – Big Data, Knowledge Management and Organisational Decision-making' presents a conceptual model that represents the link between big data, KM, decision-making and related discussion and insights. Finally, 'Conclusions' describes limitations of the work, implications of this work for academia and practice and follow-up research.

Literature Review Method

Literature Selection

We followed a systematic approach to find, filter and analyse relevant literature, using a synthesis of the methods proposed by Wolfswinkel et al. (2013) and Webster and Watson (2002). The initial search for papers first scoped the field of study bounding the search to two disciplinary areas: big data and KM. We took into consideration that the KM discipline was at the time of writing more mature than the big data discipline in terms of frameworks, methods, processes and models. In addition, we were conscious that the link between big data and KM is an emerging field, and hence were guided by our insights in both areas to further refine our set of search keywords. In the course of our interpretation of the literature, we identified the importance of organisational decision-making through human intellectual capabilities. As a result, our keywords evolved into a final set of keywords used to search relevant literature: datafication, intellectual capabilities, BA, decision-making and big data, which were used in one or more 'AND' and 'OR' combinations with the keywords: knowledge, knowledge management, knowledge management processes, tacit knowledge, and explicit knowledge.

We conducted our search using the EBSCO and Web of Science databases and used papers that resulted from Google Scholar and the Open University search engine. In addition, we concentrated also on KM journals we were familiar with from our own research and based on Serenko and Bontis's (2022) ranking list of top 3 KM journals, e.g. *Journal of Knowledge Management* (JKM), *Knowledge Management Research and Practice* (KMRP) and *Knowledge and Process Management* (KPM). Our refined search criteria further narrowed down the papers to English, peer-reviewed papers from 2014 to 2021, but we also included highly cited papers considered topical from earlier years. Our multi-method search approach resulted in papers that were filtered on title and selected finally based on the alignment of its abstract to the paper's research question. A mix of 62 conceptual and empirical papers were used in our analysis and interpretation to shape the outcomes of this book chapter.

Analysis of the Literature

In analysing the final set of papers, a 3× step coding process proposed in Wolfswinkel et al. (2013) and used in qualitative research (Strauss and Corbin, 1998) was followed. Open themes describing the link between big data, KM and decision-making were first identified. Thereafter, we clustered the open themes into meaningful categories in line with the process suggested by Gioia and Hamilton (2013) and Strauss and Corbin (1998). We report on the interpreted themes as five relevant sub-sections in the next section.

Literature Background

Development of the KM Discipline

Central to the KM literature is the important distinction between tacit and explicit knowledge in organisations and its relation to business strategy, organisational development, the use of ICTs, protection of knowledge and organisational decision-making amongst others (Alavi and Leidner, 2001; Hislop et al., 2018; Jasimuddin et al., 2005; Venkitachalam and Busch, 2012). The sharing and transfer of knowledge within and across firm boundaries and entities enabled by ICT and human perspectives have been the most researched knowledge processes in the KM literature. Related to knowledge sharing is the ability of individuals to absorb new knowledge for decision-making and new knowledge creation (Malhotra et al., 2005; Martin-de Castro et al., 2015).

Since the beginning of the 1990s, KM has developed into an important management field that increases our understanding of the vital role of knowledge as an organisational asset (Alavi and Leidner, 2001; Ruggles, 1998). Ever since the conceptualisation of Nonaka's knowledge creation theory (1991a, 1991b, 1994), and Spender and Grant's (1996) view of knowledge as a key resource (Barney, 1991) for strategic decision-making, the KM discipline has contributed several theories and models related to identifying, capturing, sharing, evaluating, retrieving, and reusing an organisation's knowledge assets (Alavi and Leidner, 2001; Watson and Hewett, 2006). Through the application and use of these knowledge-based theories in combination with ICTs and the management literature, KM has tried to fulfil a key role in explaining the importance of knowledge for decision-making in organisations.

In the 21st century, the KM discipline emphasises knowledge as a key asset that gives organisations the capability to retain a competitive edge through product and service innovation (Grant, 1996). Subramaniam and Youndt (2005) indicate that an organisation's ability to effectively use its knowledge resources is closely linked to its ability to make timely strategic decisions to create value in the environment where it operates. More specifically, organisational decision-making relates to an organisation's collective know-how and ability to utilise its knowledge resources to create and develop new business models, routines, strategies and adapt to its environment and create value through its products and services.

The inherent nature of organisational know-how includes human tacit knowledge, which is difficult to articulate but is part of the individual and collective courses of action in decision-making that generates value in the market. Institutionalised knowledge embedded and encoded in routines and procedures over time resides as explicit knowledge in ICTs (Jasimuddin et al., 2005; Schneider, 2018). Explicit knowledge is useful for humans to recall former knowledge experiences and actions to recreate and reconstruct experiences that are valuable in organisational decision-making. In general, organisational knowledge is a firm's most valuable assets, the know-how that exists collectively in a firm's employees and their interactions constitute unique knowledge and competences that organisations apply to solve unique problems allow firms to realise and maintain its competitiveness (Bontis, 2001; Campos, Dias Teixeira and Correia, 2020).

Data and the Processing of Big Data

Data, whether a limited dataset or big data, is processed into information. Data consists of bare facts, characters or symbols that turn into information once processed by computers. Data can be structured (highly specific, stored in a predefined format) or unstructured (consists of varied types of data such as text, images, audio and web content) (Sharda et al., 2018). The processing of data into information has evolved over decades into many different tools, techniques and methods. The tools have further evolved to specifically support pre-processing and preparation of big data so that it is ready for processing into information. Examples include tools to consolidate, cleanse, transform and reduce data (the so-called data 'life-cycle', see Sharda et al., 2018). Once ready for processing, mathematical and statistical techniques have gained more recognition as enabling tools to recognise patterns in large volumes of data and solve specific business problems. At present, the three main BA types are descriptive, predictive and prescriptive, each drawing on different statistical methods to process big data (Akter et al., 2019; Sharda et al., 2018) (see Figure 9.1).

Descriptive analytics, enabled by business reports, dashboards, scorecards and large data sets from data warehouses, is used to solve problems asking: 'what is the average expenditure per household' and 'how do the means between two datasets compare'-type questions. Outcomes are averages, means or standard deviations of data sets for well-defined business problems. Predictive analytics is enabled by data, text, web mining and forecasting. More complex statistical methods such as linear and complex regression, factor analysis and forecasting models are used to predict future events through answers to questions such as: 'how many sales referrals will I get next month' and 'how many calls will I get tomorrow'? Thirdly, prescriptive analytics is enabled by optimisation and simulation techniques, decision-modelling and expert systems. Questions asked are 'what shall we do to avoid ….', 'how should we plan... ', and 'must we consider…? Outcomes are best possible business

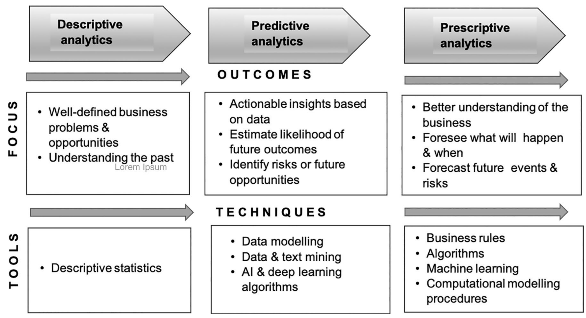

Figure 9.1 Business Analytics Types, Focus and Tools

decisions and actions for business problems. Prescriptive analytics deals with issues that raise questions about actions that need or need not be taken, what the right or wrong course of action is, or what is good or bad for a specific situation.

The data, information and knowledge hierarchy has been described frequently in the KM, organisational development and management literatures. Instead of focusing on this hierarchy, it would be more meaningful to describe the role of big data in this hierarchy. When conceptualising big data, the three 'VVV'[2] properties of big data (i.e. volume, variety and velocity) are distinguished (Akter et al., 2019; Chen, Chiang & Storey, 2012; Sharda et al., (2018). Volume refers to large quantities of data created on a daily basis worldwide. Variety refers to different types of data being created, i.e. data in traditional forms (in databases), and non-traditional forms, i.e. data created through social media, IoT devices and wearables with data as video, text, audio and graphics. Velocity refers to the speed at which data is generated with some data generated in real time (e.g. Twitter or Facebook feeds) that requires distributed processing, while other data is generated less frequently over time. The processing of big data into information, therefore, gives more insights into past experiences and trends, particularly if this data is presented visually.

From Big Data to Knowledge

Although the big data and KM link is not yet fully established from a KM perspective, recent literature acknowledges the value of big data in effective decision-making and improving business operations such as in marketing and supply chain (Chen et al., 2012 and Davenport, 2013). For example, the processing of data from social media channels can provide many new insights to marketers, e.g. how different customers react to specific advertising, what they like to see and more. This allows marketing companies to customise their advertising efforts to specific users. Big data and BA can therefore, through data mining and machine learning, provide many new insights that have not been possible before. These insights allow many organisations to make more informed decisions and help to further develop value and competitive advantage. The emergence of platform-based business models and application of BA help organisations to improve their services to customers or clients. One example is Amazon whose aim is to effectively serve customers while also learning what customers find trendy for future offerings and services.

Big data and BA have a different perspective on knowledge compared with the KM discipline. Blackler (1995) positions knowledge as embedded in human minds and embodied in human actions to differentiate between tacit and explicit knowledge. Tacit knowledge (know-how) is rooted in action and experience, is difficult to imitate, exists in human minds and has both cognitive and technical elements (Nonaka, 1994). Tacit knowledge is gained through extensive expertise that comprises interaction between knowing and doing (Jasimuddin et al., 2005; Schultze and Stabell, 2004). Tacit knowledge is therefore a unique intellectual capability and an essential cognitive resource contributing to innovation. In contrast, explicit knowledge can be articulated, uttered, codified and communicated in written, symbolic or natural language (Alavi and Leidner, 2001). Examples are routines captured in digital form, rules of thumb, heuristics, practical guidelines or any other form that can be accessed or used by others (e.g. digital artefacts). Explicit knowledge is declarative knowledge (or 'know-what') that can also exist individually or collectively, e.g. in a team or a group who has worked together and share experiences as a result of complex problem-solving as a team over time.

Explicit knowledge is a basis for new knowledge creation, and drawing on the SECI model (Nonaka, 1994), the articulation of tacit knowledge into a digital explicit form makes explicit knowledge available through ICTs to others in an organisation, enabling access to and internalising explicit knowledge. Explicit knowledge is not considered information per se, but actionable knowledge enabling its recipients to create new knowledge through knowing and acting. The internalisation of explicit knowledge can also spur the creation of new knowledge in a totally different knowledge context. Knowledge is therefore dynamic (Venkitachalam and Willmott, 2015) and processes of making tacit knowledge explicit, allows for synthesising, incorporating and applying knowledge in new scenarios. So, in the context of big data and BA, literature sources refer to computers having the ability to "*… create new knowledge on its own…*" (Muller et al., 2019), while BA techniques can '*discover*' and '*extract*' knowledge from big data through data mining algorithms, pattern matching and machine learning (Sharda et al., 2018).

Considering the definition, dimensions and nature of knowledge found in the KM literature, there is a vast difference between the conceptualisation of knowledge in big data and BA versus the meaning of knowledge in the KM discipline (Tian, 2017). Knowledge in big data and BA is an outcome of the algorithmic pattern matching and data mining that enables organisations to better understand patterns in the data. Hence, the challenge is to discern whether this 'knowledge' is indeed explicit or tacit knowledge, i.e. actionable insights that first lead to a deeper understanding of one context to another, and secondly leads to more effective decision-making in a knowledge context. At this point of contextual shift and dependency, there is no clear picture whether this context-bounded knowledge can be clearly understood from an empirical (big data) perspective.

The Context of Knowledge

One of the most important characteristics of knowledge is that it is sticky and tied to a specific context (Meacham, 1983; Tsoukas, 1996). Detached from its context, knowledge makes no sense and loses its unique value. Take for example the unique jargon that develops in a fibromyalgia health community that frequently interacts in the Reddit online social media group. The illness has unique symptoms, traits and labels for specific things, e.g. the chronic illness community uses the tag 'spoonie' to explain one's lack of energy. Too much energy spent in the morning on a day might leave one with limited energy levels (fewer 'spoons') for the afternoon/evening. The word 'spoonie' has no meaning when used alone and out of context, but in the context of chronic illness, this term has a very specific context and meaning.

The importance of a knowledge context is therefore a central underpinning of the data-information-knowledge hierarchy. Tsoukas (1996) describes an organisation as a distributed knowledge system whereby the use of knowledge is not known by a single agent alone. The knowledge an organisation needs to draw on is indeterminate and continually emerging (Venkitachalam and Willmott, 2016). As a result, knowledge is not self-contained but consists of the stock of: (i) role-related normative expectations, (ii) dispositions formed as a result of social networking and (iii) local knowledge related to specific situations or circumstances related to time and place. In this context, Tsoukas (1996) highlights four types of organisational knowledge and they are: (i) conscious explicit knowledge of an individual, (ii) objectified knowledge, which is explicit and held by the organisation (as in an organisational memory), (iii) automatic preconscious individual knowledge and (iv) collective highly context-dependent knowledge, which is present in the practices of an organisation. Of importance is thus knowledge of a specific context held individually or shared collectively in an organisation as a result of *shared practices and know-how* acquired over time through learning.

Human and Organisational Decision-Making

Extant BA literature expresses the need for practitioner knowledge in statistical methods, models, tools and techniques to improve decision-making (Muller et al., 2019). Decision-making is a complex concept rooted in psychology and comprises a higher order of thinking that involves human intellectual capabilities (Pohl, 2008). Intellectual ability is an individual's exceptional capability that evolves through a set of cognitive process, i.e. the ability to find and solve problems, reasoning, including spatial reasoning, memory use and recall, the ability to manipulate abstract ideas and make connections (Jaques, 1986). Intellectual ability evolves over time through an individual's rate of learning and experiences in a specific knowledge area, hence human cognition is often tied to a specific knowledge context resulting from prolonged exposure to problem-solving through acting and learning (Pohl, 2008).

Intellectual capability manifests as cognitive processes individuals draw on to solve complex problems through planning and carrying out goal-directed activities. Organisational decision-making therefore requires the combination of intellectual capabilities of multiple knowledge sources (both tacit and explicit). In an age of more competition, the nature of organisational problem-solving has become more complex, hence decision-making in an era of big data requires mechanisms that integrate machine knowledge with human intellectual capability. Kurzweil articulated this need way back in 1999 using Brockman's words (2002), stating '*…we are entering a new era …. it's a merger between human intelligence and machine intelligence…*'. With the advent of BA, there is a gap in the literature that explains how big data links to KM from an organisational decision-making perspective.

Conceptual Model – Big Data, Knowledge Management and Organisational Decision-making

Based on the preceding discussion, the conceptual model in Figure 9.2 attempts to illustrate the outcome of the BA knowledge discovery and pattern-matching activities that interprets large data sets yielding actionable insights from this data. BA is becoming increasingly adopted to support organisational decision-making (Akter et al., 2019). As explained before, the outcome of the BA process's 'machine knowledge' is used in the organisational decision-making process. This knowledge is not yet the explicit knowledge of KM that represents a specific knowledge context.

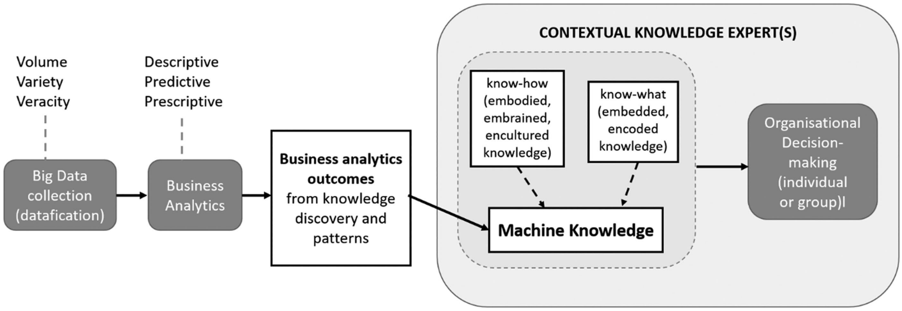

Figure 9.2 Link between Big Data and Organisational Decision-Making

Based on our analysis of the literature indicating the gap in understanding the link between big data and KM, our model illustrates that the link between machine intelligence and human intelligence needs to be brokered through the specialist know-how and know-what of *contextual knowledge experts*. Their expertise is essential to link big data and KM and solve complex business problems for organisational decision-making. To further explain this gap, we develop the following five insights derived from the literature, which are discussed in the section that follows:

Take as an example, studies as that of O'Connor and Kelly (2017) and Sumbal et al. (2017) and scholars like Pauleen's (2017) interview with one of the global experts (David Snowden) in the field of KM caution that the role of human know-how/judgement cannot be overlooked when understanding the link between big data and KM in decision-making. Snowden illustrates the case of recruitment, where there is growing evidence of using BA algorithms/big data tools to determine which candidate should attend a job interview. Snowden argues:

> *People these days are actually using algorithms to determine which CVs get put forward for an interview. You can now buy an algorithm that will improve your CV, so it's more likely to get accepted (by an algorithm designed to find acceptable CVs). This is just getting nonsensical. And it's removing human judgment from the process. And if KM is about one thing, it's about emphasizing the value of human judgment and human sensemaking*
>
> *(Pauleen, 2017, p.13)*

This aspect of human judgement and sensemaking a particular context/s can be effectively managed by (what we conceptualise in this chapter as) 'Contextual knowledge experts'. Hence,

Insight 1: *Contextual knowledge experts are essential to bridge the big data–KM gap for decision-making in organisations.*

When considering the limitation of raw data source/machine knowledge generated from a BA process (O'Connor and Kelly, 2017; Sumbal et al., 2017), consider the case of water engineers monitoring water pumps in reservoirs (Pauleen, 2017). Snowden explains his work with,

> *water engineers (allowed) them to report any micro anomaly they see – something they wouldn't conventionally report. They can take a picture and interpret it, for example onto a triangle, which has "it tastes wrong, it feels wrong, it looks wrong...* and they're radically increasing the number of minor incidents reported by allowing the deliberate ambiguity of interpretation.
>
> *(Pauleen, 2017, p. 14)*

This example is relevant evidence (deliberate ambiguity of interpretation) of how the engineers are using their years of experience and contextual know-what and know-how to make a decision concerning 'micro anomaly' or unusual developments and changes in water pump operation. To illustrate further, the water engineers as 'contextual knowledge experts' are allowed to go beyond the analytics generated machine knowledge to come to a decision-making pertaining to water quality and pump operation. Hence,

Insight 2: *Human judgement exists as actionable knowledge in the minds of contextual knowledge experts which is difficult to codify but necessary to increase the outcomes of organisational decision-making* and

Insight 3: *The resulting 'machine knowledge' from the BA process is insufficient on its own for organisational decision-making.*

Based on the above instances that emphasise the significance of context-dependent knowledge, whether the case of CV shortlisting or water pump operation, it is essential to have the human experience and judgement as the embedded and embrained qualities of human knowledge evident in contextual knowledge experts as 'recruitment specialists' and 'water engineers' in the process of decision-making. Perhaps, decisions are not entirely based on one individual's contextual (embodied) knowledge, but the distributed nature of encultured knowledge based on many 'contextual knowledge experts' that aid for better decision-making for organisational problems. Hence,

Insight 4: *The distributed nature of knowledge in the form of intellectual capability divided between different contextual knowledge experts is necessary to improve organisational decision-making* and

Insight 5: *Machine knowledge in combination with know-what and know-how of contextual knowledge experts (i.e. embrained, embodied, embedded, encoded and enculture knowledge) may significantly improve organisational decision-making.*

Conclusions

This chapter aims to explain the link between big data and KM and suggests the central role of human agency in the form of *contextual knowledge experts* to bridge the gap between big data and KM. Based on a conceptual model derived from the literature, five key arguments are proposed that explain how this gap can be bridged.

This chapter has the following limitations. First, this study is nascent and there is a need to further develop and test the proposed conceptual model. This could be tackled in two phases, first through a qualitative study involving a series of interviews with key decision-makers in a number of different competitive organisations across cultural contexts around the globe. Future research could be refined and/or the conceptual model could be extended, which could then be followed up with a larger quantitative study to further test and develop new propositions. In doing so, the coverage of the intricacies of the decision-making discipline that is currently of limited scope in this chapter can be covered in more depth in future studies.

From a research perspective, the conceptual model and the five insights have implications for academics and practitioners. For researchers, the link between BA and KM is worth exploring in particular to determine the key mechanisms that improve and impact the quality of decision-making enabled by BA. In addition, the limitations of machine knowledge can be determined in order to develop a decision-making model that bridges the big data–KM gap. For practitioners, this work has implications in the sense that contextual knowledge experts need to be identified to shape and frame the big data–KM process and to confirm their proactive role in the organisational decision-making process. Both these academic and practical implications suggest avenues for further research.

Notes

1 Business Analytics involves the analysis of data to make key business decisions in an organisation
2 Three additional V's of data (veracity, value and variability) are often added to volume, variety and velocity

References

Adler, P. S., & Kwon, S. W. (2002). Social Capital: Prospects for a New Concept. *Academy of Management Review*, 27(1), 17–40.

Akter, S., Bandara, R., Hani, U., Wamba, S. F., Foropon, C., & Papadopoulos, T. (2019). Analytics-Based Decision-Making for Service Systems: A Qualitative Study and Agenda for Future Research. *International Journal of Information Management*, 48, 85–95.

Alavi, M., & Leidner, D. E. (2001). Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. *MIS Quarterly*, 107–136.

Barney, J. (1991) Firm Resources and Sustained Competitive Advantage. *Journal of Management*. 17(1), 99–120.

Blackler, F. (1995). Knowledge, Knowledge Work and Organizations: An Overview and Interpretation. *Organization Studies*, 16(6), 1021–1046.

Bontis, N. (2001). Assessing Knowledge Assets: A Review of the Models Used to Measure Intellectual capital. *International Journal of Management Reviews*, 3(1), 41–60.

Bosua, R., & Scheepers, R. (2007). Towards a Model to Explain Knowledge Sharing in Complex Organisational Environments. *Knowledge Management Research & Practice*, 5(2), 93–109.

Bosua, R., & Venkitachalam, K. (2013). Aligning Strategies and Processes in Knowledge Management: A Framework. *Journal of Knowledge Management*, 17(3), 331–346.

Brockman J. (2002). The Singularity: a talk with Ray Kurzweil, Edge 99 – March 25, 2002, Edge Foundation, (http://www.edge.org)

Campos, S., Dias, J.G., Teixeira, M.R., & Correia, R.J. (2020). The Link Between Intellectual Capital and Business Performance: A Mediation Chain Approach. *Journal of Intellectual Capital*, DOI 10.1108/JIC-12-2019-0302

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, 36, 1165–1188.

Chen, C.L. Philip, & Zhang, C-Y. (2016) Data-intensive Applications, Challenges, Techniques and Technologies: A Survey on Big Data. *Information Sciences,* http://dx.doi.org/10.1016/j.ins.2014.01.015

Cross, R., Parker, A., Prusak, L., & Borgatti, S. P. (2001). Knowing What We Know: Supporting Knowledge Creation and Sharing in Social Networks. *Organizational Dynamics*, 30(2), 100–120.

Davenport, T. H. (2013). Analytics 3.0. *Harvard Business Review*, 91(12), 64–72.

Gartner (2020). 100 Data and Analytics Predictions through 2024, Accessed on 15 Dec 2020 from: https://www.gartner.com/en/information-technology/trends/100-data-and-analytics-predictions-through-2024-pd?utm_source=google&utm_medium=cpc&utm_campaign=RM_EMEA_2020_ITTRND_CPC_LG1_H2-GTS-AOC&utm_adgroup=113671253751&utm_term=data%20analytics&ad=476738599130&gclid=CjwKCAiA_eb-BRB2EiwAGBnXXu-LbRLjzHZn1DaV-ZiRm19Z3EJR-NMl55bf1ksIGa97rGx5DwZmXyhoC-w8QAvD_BwE

Gioia, D.A., Corley, K.G. & Hamilton, A.L. (2013). Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology. *Organizational Research Methods*, 16(1), 15–31.

Grant, R. M. (1996). Toward a Knowledge-based Theory of the Firm. *Strategic Management Journal*, 17(S2), 109–122.

Hansen, M. T., Nohria, N., & Tierney, T. (1999). What's your Strategy for Managing Knowledge. *The Knowledge Management Yearbook 2000–2001*, 77(2), 106–116.

Heisig, P., Suraj, O.A., Kianto, A., Kemboi, C., Arrau, G.P., & Easa, N.E. (2016). Knowledge Management and Business Performance: Global Experts' Views on Future Research Needs, *Journal of Knowledge Management*, 20(6), 1169–1198,

Hernán, M. A., Hsu, J., & Healy, B. (2019). A Second Chance to Get Causal Inference Right: a Classification of Data Science Tasks. *Chance*, 32(1), 42–49.

Hislop, D., Bosua, R., & Helms, R. (2018). *Knowledge Management in Organisations: A Critical Introduction*. Oxford University Press: Oxford, UK.

Jasimuddin, S. M., Klein, J. H., & Connell, C. (2005). The Paradox of Using Tacit and Explicit Knowledge: Strategies to Face Dilemmas. *Management Decision*, 43(1), 102–112.
Jaques, E. (1986). The Development of Intellectual Capability: A Discussion of Stratified Systems Theory. *The Journal of Applied Behavioral Science*, 22(4), 361–383.
Kurzweil, R. (1999). Spiritual Machines: The Merging of Man and Machine. *The Futurist*, 33(9), 16–21.
Litvaj, I., & Stancekova, D. (2015). Decision-making, and their Relation to the Knowledge Management, Use of Knowledge Management in Decision-making. *Procedia Economics and Finance*, 23, 467–472.
Lycett, M. (2013). 'Datafication': Making Sense of (Big) Data in a Complex World. *European Journal of Information Systems*, 22(4), 1–7.
Malhotra, A., Gosain, S., & Sawy, O. A. E. (2005). Absorptive Capacity Configurations in Supply Chains: Gearing for Partner-Enabled Market Knowledge Creation. *MIS Quarterly*, 29(1), 145–187.
Marabelli, M. & Newell, S. (2014). Knowing, Power and Materiality: A Critical Review and Reconceptualization of Absorptive Capacity. *International Journal of Management Reviews*, 16(4), 479–499.
Martín-de Castro, G. (2015). Knowledge Management and Innovation in Knowledge-Based and High-Tech Industrial Markets: The Role of Openness and Absorptive Capacity. *Industrial Marketing Management*, 47, 143–146.
Meacham, J. A. (1983). Wisdom and the Context of Knowledge: Knowing That One Doesn't Know. *On the Development of Developmental Psychology*, 8, 111–134.
Muller, M., Lange, I., Wang, D., Piorkowski, D., Tsay, J., Liao, V.Q., Dugan, C., & Erikson, T. (2019). How Data Science Workers Work with Data: Discovery, Capture, Curation, Design, Creation. In *CHI 2019*, 4–9 May, Glasgow, Scotland, U.K. DOI: https: doi.org/10.11
Nahapiet, J., & Ghoshal, S. (1998). Social Capital, Intellectual Capital, and the Organizational Advantage. *The Academy of Management Review*, 23(2), 242–266.
Nonaka, I. (1991a). The Knowledge-Creating Company. *Harvard Business Review*, November–December, 96–104.
Nonaka, I. (1991b). Managing the Firm as an Information Creation Process. In Meindl, J.R., Cary, R.L., & Puffer, S.M. (Eds), *Advances in Information Processing in Organizations*. Greenwich, CT, London: JAI Press Inc., 239–275.
Nonaka, I. (1994). A Dynamic Theory of Organizational Knowledge Creation. *Organization Science*, 5(1), 14–37.
Nonaka, I. (2007). The Knowledge-Creating Company. *Managing for the Long Term, Best of HBR,* July–August, 162–171.
Nonaka, I. & Hirose, A. (2015). Practical Strategy as Co-Creating Collective Narrative: A Perspective of Organizational Knowledge Creating Theory. *Kindai Management Review*, 3, 9–24.
Nonaka, I., & Toyama, R. (2003). The Knowledge-Creating Theory Revisited: knowledge Creation as a Synthesizing Process. *Knowledge Management Research & Practice*, 1(1), 2–10.
Nonaka, I. & Toyama, R. (2005). The Theory of the Knowledge-Creating Firm: Subjectivity, Objectivity and Synthesis. *Industrial and Corporate Change*, 14(3), 419–436.
O'Connor, & Kelly, S. (2017). Facilitating Knowledge Management through Filtered Big Data: SME Competitiveness in an Agri-Food Sector. *Journal of Knowledge Management*, 21(1), 156–179.
Pauleen, D. (2017). Dave Snowden on KM and Big Data/Analytics: Interview with David J. Pauleen. *Journal of Knowledge Management*, 21(1), 12–17.
Pohl, J. (2008). Cognitive Elements of Human Decision-making. *Studies in Computational Intelligence (SCI),* 97, 41–76.
Razzaq, S., Shujahat, M., Hussain, S., Nawaz, F., Wang, M., Ali, M., & Tehseen, S. (2019). Knowledge management, Organizational Commitment and Knowledge-Worker Performance: The neglected role of knowledge management in the public sector. *Business Process Management Journal*, 25(5), 923–947.
Ruggles, R. (1998). The State of the Notion: Knowledge Management in Practice. *California Management Review*, 40(3), 80–89.
Sadowski, J. (2019). When Data is Capital: Datafication, Accumulation, and Extraction. *Big Data & Society*, 6(1), pp. 1–12, 2053951718820549.
Schneider, M. (2018). Digitalization of Production, Human Capital, and Organizational Capital. In *The Impact of Digitalization in the Workplace* (pp. 39–52). Cham: Springer.

Schultze, U., & Stabell, C. (2004). Knowing What You Don't Know? Discourses and Contradictions in Knowledge Management Research. *Journal of Management Studies*, 41(4), 549–573.

Serenko, A., & Bontis, N. (2022). Global Ranking of Knowledge Management and Intellectual Capital Academic Journals: A 2021 Update. *Journal of Knowledge Management*. 26(1), 126–145.

Sharda, R., Delen, D., & Turban, E. (2018). *Business Intelligence, Analytics and Data Science: A Managerial Perspective*, 4th edition, Pearson Global Edition, U.K., 512 p.

Spender, J. C., & Grant, R. M. (1996). Knowledge and the Firm: Overview. *Strategic Management Journal*, 17(S2), 5–9.

Stodden, V. (2020). The Data Science Life Cycle: A Disciplined Approach to Advancing Data Science as a Science. *Communications of the ACM*, 63(7), 58–65.

Strauss, A., & Corbin, J. M. (1997). *Grounded Theory in Practice*. Thousand Oaks, CA: Sage Publications.

Subramaniam, M., & Youndt, M. A. (2005). The Influence of Intellectual Capital on the Types of Innovative Capabilities. *Academy of Management Journal*, 48(3), 450–463.

Sumbal, M., Tsui, E., & See-to, E. (2017). Interrelationship between Big Data and Knowledge Management: An Exploratory Study in the Oil and Gas Sector. *Journal of Knowledge Management*, 21(1), 180–196.

Tian, X. (2017). Big Data and Knowledge Management: A Case of Déjà Vu or Back to the Future? *Journal of Knowledge Management*, 21(1), 113–131.

Tsoukas, H. (1996). The Firm as a Distributed Knowledge System: A Constructionist Approach. *Strategic Management Journal*, 17(S2), 11–25

Venkitachalam, K., & Busch, P. (2012). Tacit Knowledge: Review and Possible Research Directions. *Journal of Knowledge Management*, 16(2), 357–372.

Venkitachalam, K., & Willmott, H. (2015). Factors Shaping Organizational Dynamics in Strategic Knowledge Management. *Knowledge Management Research & Practice*, 13(3), 344–359.

Venkitachalam, K., & Willmott, H. (2016). Determining Strategic Shifts between Codification and Personalization in Operational Environments. *Journal of Strategy and Management*, 9(1), 2–14.

Vicario, G., & Coleman, S. (2020). A Review of Data Science in Business and Industry and A Future View. *Applied Stochastic Models in Business and Industry*, 36(1), 6–18.

Watson, S., & Hewett, K. (2006). A Multi-Theoretical Model of Knowledge Transfer in Organizations: Determinants of Knowledge Contribution and Knowledge Reuse. *Journal of Management Studies*, 43(2), 141–173.

Webster, J., & Watson, R. T. (2002). Analyzing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly*, 26(2), xiii–xxiii.

Wolfswinkel, J. F., Furtmueller, E., & Wilderom, C. P. (2013). Using Grounded Theory as a Method for Rigorously Reviewing Literature. *European Journal of Information Systems*, 22(1), 45–55.