Spring 6-29-2022

Understanding Big Data Driven Decision Making in British Financial Organisations

Mohammed Banu Ali
University of Salford, mow23839@gmail.com

Trevor Wood-Harper
University of Manchester, atwh@manchester.ac.uk

Robert Wood
University of Bolton, r.wood@bolton.ac.uk

Understanding Big Data Driven Decision-Making in British Financial Organisations

Mohammed Banu Ali,
mow23839@gmail.com
University of Salford

Trevor Wood-Harper,
atwh@manchester.ac.uk
University of Manchester

Robert Wood,
r.wood@bolton.ac.uk
University of Bolton

Abstract
Although big data can enhance financial decision-making in organisations (e.g., predicting financial performance), the epistemological argument of big data is that knowledge or truth which relies on (big) data needs to first be generated to make key decisions. Despite big data having the potential to enhance organisational decision-making, little empirical research has been conducted on the epistemology of big data driven financial decision-making. This paper uses knowledge management reliability (KMR) theory, as well as an interpretive strategy and expert interviews to contribute to the existing body of knowledge to understand the epistemological implications of decision-making with large data sets to predict financial performance in British banks. Our findings reveal a shift toward knowledge based data-driven decision making for predicting financial performance.

Keywords: Big data, Epistemology, Decision Making, Knowledge Management, Financial Performance, Stress Test

1.0 Introduction

There is a strong thread running through the literature on big data that more data will result in rapid innovation. Recent figures show that roughly two-thirds of organisations around the world in 2021 have a data-driven decision-making initiative in place to assist with performance related issues (Statista, 2022), suggesting that big data has become the cornerstone of organisational decision making. These figures support Desouza and Jacob (2017) and O'Malley's (2014) theory that big data can enhance organisational decision-making. Kitchin (2014) argues in a seminal article that what distinguishes big data from regular data is the epistemic positioning, not the volume. The branch of philosophy known as epistemology is concerned with the nature of knowledge (Anderson & Johnston, 2017). Thus, epistemological development refers to the process by which people's conceptions of the nature of knowledge evolve as they mature. When it comes to big data, this epistemology of big data can affect organisational decision making using large data sets to predict financial performance. Despite big data having the potential to enhance organisational decision-making, little empirical research has been conducted on the use of big data, particularly in the financial context (de Sousa et al., 2019). Hence, this study uses a branch of knowledge management theories known as "knowledge management reliability theory" (KMR) to understand the phenomenon.

This study examines a recent example of increasingly (big) data-driven decision making to gain a better understanding of how big data is used in British banks using a banking stress test as a case study. The stress test, which was developed in the aftermath of the 2008–2009 financial and economic crisis, which caused a huge economic crash, is now conducted biannually on financial institutions in the UK, Europe and the United States. According to the Bank of England, the usual annual stress test or the annual cyclical scenario (ACS), simulates a crisis scenario for banks, which serves as an indicator of their health and predicts financial performance (Bank of England, 2021). At first glance, it appears as though the stress test is a bottom-up exercise in which each bank calculates its own impact on a crisis scenario. When banks submit data, it is subjected to a Quality Assurance (QA) process to ensure that they are not abusing the system by "gaming." Banks simulate how a financial or economic crisis would affect banks in the QA process by utilising all data collected from banks and other publicly available data. Regulators adopt a big data mindset that banks do not share, impairing the regulatory process and casting doubt on notions of accountability and transparency.

The following sections summarise the pertinent literature on big data and knowledge management reliability theory, before demonstrating how the UK banking stress test reflects this shift in epistemic mindset and how it affects decision-making. Hence, the purpose of this paper is to contribute to the existing body of knowledge by conducting an empirical investigation into understanding the epistemological implications of making decisions with large data sets to predict financial performance. Hence, we propose this following research question: "*How are key financial decisions made from knowledge generated by big data to predict financial performance?*"

2.0 Theoretical Background

2.1 Epistemology of Big Data Driven Decision-Making

Large volumes of data, dubbed "big data," could provide unprecedented opportunities to gain and maintain competitive advantage through making more informed policy decisions (Wiener et al., 2020). However, what is big data? The term "big data" is a misnomer in many ways. To begin, "majority" is a relative term in an era of unprecedented technological progress. With standard software, desktop computers can now analyse 'big' data sets that previously required supercomputers (Manovich, 2011). The sheer volume of data is only one of several characteristics frequently associated with big data. Despite the lack of consensus on what big data is, the majority of authors agree on five "Vs": volume, variety, and velocity, veracity and value (Chan & Moses, 2016; Salganik, 2017). Apart from its sheer volume, the data is typically in a variety of formats and is generated at a high rate and at certain degrees of quality to meet a certain outcome (e.g. performance, decision making, profit etc.). However, Hirschheim (2021) argues that the availability of large data sets does not always help to make better decisions, but we need to rely on it to obtain knowledge. The concept of dataism helps to shed some light on the reliance of data.

The popular historian Yuval Harari coined the term 'dataism' to describe this reliance on big data. Because humans are no longer capable of distilling enormous flows of data into information, knowledge, or wisdom, the task of data processing should be delegated to computational algorithms with far greater capacity than the human brain" (Harari, 2016, p. 368). Another aspect of dataism is a (often blind) faith in the agents responsible for collecting, interpreting, and sharing this data. Van Dijck (2014) elucidates this further. While Redden (2015) points out that big data findings are prioritised over other methods of information production, they shape the reality they measure in the process. Additionally, there is the risk of reinforcing neoliberal rationalities and instrumental thinking, which she warns can be detrimental. As a result, big data goes far beyond the three Vs. Dataism, the dataification of reality, and the use of big data all have a significant epistemological component (Kitchin, 2014; Yeung, 2018). Boyd and Crawford (2012) assert that big data reframes critical questions about the nature of knowledge, how we should engage with information, and the nature and categorization of reality. To summarise, this demonstrates that trust in big data is based on the epistemological premise that more data is needed to comprehend, predict, and classify the world.

The epistemology of big data refers to a philosophy of knowledge or truth that heavily relies on (big) data to generate knowledge or truth. The term ‘epistemology of big data’ is used because the gap between theory and data is continuous. For example, the application of data and knowledge management-related theory in economics can range from solely relying on the assumed theoretical inverse relationship between inflation and unemployment to insurance companies determining premiums solely through algorithms. The shift in mindset is particularly interesting, regardless of the degree of data reliance. However, much of the criticism levelled at big data stems from this epistemological shift toward a big data mentality (Kitchin, 2014; Symons & Alvarado, 2016). A big data mindset is viewed as a threat to the quality of knowledge. Often, the issue boils down to determining the level of transparency required for making a particular decision. As a result, there is a need for forward-thinking initiatives and technical solutions to enhance fairness, accountability, and transparency (Lepri et al., 2018). However, much work remains to be done in this area. The opportunity to fill this gap comes from focussing on big data as large data sets and how it facilitates decision-making from the knowledge drawn from this data. It is not the sheer size of the datasets that distinguishes big data from regular data (Kitchin, 2014; Mayer-Schönberger & Redden, 2015), but rather the epistemological foundations upon which this data is used to generate knowledge claims. Hence, this study uses knowledge management reliability (KMR) theory to explore this phenomenon.

2.2 KMR Theory

KMR theory is a relatively new theory developed by Mazdeh and Hesamamiri (2014, p.107-8) that aims to understand how "increased mindfulness positively affects reliability of KM (as a system of processes in a context of culture, technology, and organizational structure) through minimising and eliminating the risk of failures occurred in KM process and infrastructure capabilities and results in increased organisational performance." Although the theory incorporates various concepts more inclined towards internal performance of financial firms as opposed to external performance of economies, this paper argues that the theory is pertinent to both given the relevant concepts and constructs, such as financial and process performance, which are highly relevant to the epistemological implications of decision-making using big data to predict financial performance.

Based on the knowledge management and performance constructs of KMR theory, three characteristics define this epistemological mindset (Mayer-Schönberger & Cukier, 2013). To begin, there is the concept of comprehensiveness; the notion that a large amount of data can provide a comprehensive view of an event's characteristics. The second concept is that of disorder. Regardless of the world's complexity or messiness by collecting large amounts of (messy) data, which will automatically reveal established patterns. The third concept, the triumph can be used to instantly determine which model fits the data the best or a data-driven representation of reality. Hence, the empiricist epistemological judgement about what types of knowledge are useful and valid is more extreme in this interpretation. Our findings are framed on these three concepts.

3.0 Research Methodology

This study uses KMR theory to understand the epistemological implications of making decisions with large data sets to predict financial performance. This study employs an interpretive strategy or qualitative methods (Schwartz-Shea & Yanow, 2012) to align theory with descriptive and comprehensive empirical findings (the use of big data) in order to arrive at the final conclusions. Expert interviews were conducted to gain a better understanding of how those involved in data-driven decision-making perceive this. This case is relevant because the UK banking stress test clearly demonstrates a shift toward data-driven decision making for predicting financial performance. Interviewees were chosen based on their involvement in the case to interview those who played a significant role in the study. Since there was no access to the banks, data was gathered from 2 consulting firms who had affiliations with UK banks. Each of these players recognises the importance of data-driven decision-making, and this was taken into account when interpreting the findings. By involving a diverse range of actors with varying interests and modes of reasoning, the author gained a holistic view of the issue at hand. Table 1 summarises the subjects and number of interviews. Over the course of the project, 25 people were interviewed for a total of 35 hours; we arrived at this number based on the advice of Creswell and

Creswell (2018) who recommends that researchers should conduct 20-30 interviews to yield comprehensive data.

Organisation	**Respondents**	**Interviews**	**Code**
Consultancy firm A	12	2	CFA1
		1	CFA2
		2	CFA3
		2	CFA4
		1	CFA5
		1	CFA6
		1	CFA7
		2	CFA8
		1	CFA9
		2	CFA10
		2	CFA11
		2	CFA12
Consultancy firm B	13	2	CFB1
		2	CFB2
		1	CFB3
		1	CFB4
		2	CFB5
		2	CFB6
		2	CFB7
		1	CFB8
		1	CFB9
		1	CFB10
		1	CFB11
		1	CFB12
		2	CFB13
Total:	25	35	

Table 1. Participants Summary

For practical reasons, interviews with UK banks were conducted. When interpreting the findings, it is critical to understand how people interpret data-driven decision-making in their own countries. To obtain a more complete picture, the researchers interviewed consultants across two consultancy firms situated in the UK. Firstly, potential participants were identified by contacting the managers of the consultancy firms. Additionally, the participants were obtained by emails and telephone conversations and responding to the researchers' request. The interviews were conducted in a meeting room in the firms, and were digitally recorded. Interviews were conducted until no additional information or arguments could be offered, implying that no additional information or arguments could be presented. The interviews lasted an average of 60 minutes.

With the assistance of semi-structured questions, the researchers were able to discuss the same topics with each interviewee while remining within the scope of the questions. The questions were based on the concepts of the KMR theory (comprehensive, disorder and triumph) in relation to topic of big data driven decision making. Since we framed the questions on the KMR concepts, thematic analysis was used to code and analyse the interview responses. The NVIVO software assisted with the coding of the themes. The interview transcripts were coded using emergent codes, which are close to the text, using the subjects' own vocabulary (Drisko & Maschi, 2015). As a result, the researchers were able to categorise the data into the themes of “Epistemological Implications of Data-Driven Decision-making for Comprehensive, Disorderly and Triumphant Financial Performance” and “Rethinking Big Data Driven Decision-Making Accountability and Transparency for Financial Performance”.

4.0 Results & Findings

4.1 Epistemological Implications of Data-Driven Decision-making for Comprehensive, Disorderly and Triumphant Financial Performance

During the interviews, the supervisors had no doubt about how difficult it would be to determine a bank's health. This can be explained by the idea that the world is fundamentally disordered and chaotic. As a result of this development, a new data-driven approach to risk management based decisions and a significant shift in financial supervision are possible. One participant stated:

> *"People begin to wonder, 'Oh no, how did this crisis happen,' a stress test respondent from one of the banks explained. It is possible that the supervisor handled the situation incorrectly or lacked the information necessary to anticipate it. As a result, you are left with mountainous amounts of unsatisfied requirements. To compound matters, no one knows when or where the next crisis will occur. We cannot, in my opinion, act [make decisions] as if we already know everything.” (CFA3)*

Respondents also stated that they were “increasingly attempting to leverage all available data sources, including household surveys” (CFB1), in order to gain a better understanding of the risks facing banks. The concept of comprehensiveness was instrumental in this endeavour, as was the notion that large amounts of data provided an exhaustive overview of a phenomenon's characteristics. One respondent added:

> *"The reporting requirements [for the stress test] are ridiculous. Each year, their numbers increase. Each time, they demand increasingly detailed information. We asked them, when will this arms race for data come to an end? Last year at this time, there were only 200,000 data points; now there are 350,000. Their lips were sealed around a single question: What is the alternative?" (CFB5)*

Regulators are increasingly relying on large amounts of data to help them understand how a bank is performing in the aftermath of the 2008 economic crisis. The term "regulatory big" was used to refer to regulators' increasing use of large data sets for analysis. Despite the fact that this regulatory big data does not meet the definition of big data (it does not have the volume of clicks on a popular website and is not always generated automatically), its volume is significantly greater than the summary reports regulators typically require. The concept of triumph is important here because regulators are expected to use this regulatory big data to make key decisions to bolster their control and monitoring efforts. One respondent stated:

> *"…we are expected to utilise this new regulatory-based big data to improve control and consult banks on their financial performance based on observing these performances, but the volume is too great and thus management tools or systems are needed to aid us in analysing this huge dataset to make our data-driven decisions." (CFA7)*

While the volume of data collected is critical, the epistemological shift toward a big data mindset is what distinguishes this approach. Increased data collection will inevitably result in improved results, but there needs to be tools in place to support the analysis of large datasets to make informed process and financial decisions.

The concept of disorder revealed that regulators interact with the entities they regulate by conducting a Quality Assurance (QA) process to vet banks' results, relying on all the large amounts of data they collect and semi-automated big data tools and techniques. The consultants made comments about this issue in terms of the stress tests banks have introduced:

> *"If the results of the stress test calculated are similar enough to what the banks submitted, there is a green flag. If there is a minor discrepancy, it is flagged in orange. If there is a large difference between the results, there is a red flag." (CFB9)*

The consultants also state that the banks' Joint Supervisory Teams (JSTs) are those in charge of discussing these flags with banks and resolving them. Banks can 'comply or explain', this means that either they accept the result filed or they have to explain why their calculations were correct. A respondent criticised this process:

> *"I haven't spoken to all the JST reps, only some, but I feel like most of them are there to solve the flags but they're not actually trying to understand the results. There was one time where I was trying to understand the difference between the 2016 and 2018 financial performance results for some banks, and a lot of the JST reps had no idea why their bank was doing better or worse than in 2016. They're just focused on the flags. So, in a way I'm a little disappointed about this trend." (CFA10)*

Similar sentiments came up during many of the interviews. One consultant stated that the supervisors were said to be:

> *"…overly focused on what came out of their large amounts of data, rather than understanding how banks calculated their results, and where the discrepancy came from. This was very frustrating to the banks. They felt that the QA process acted like a black box; predicting an outcome without necessarily explaining, or justifying, where that outcome comes from." (CFB1)*

The consultant also found that, to banks, supervisors seemed very uninterested in how they explained their results.

> *"…banks write 'narratives' to explain how they obtain their results. As such, there is always an explanation as to why a loan would default or why an asset has a higher or lower risk. When supervisors check these results in the top-down QA process, they do not necessarily explain or justify how their result was obtained." (CFA10)*

This obscurity has two dimensions: on the one hand the banks were not very transparent about their reasoning overall, on the other, the banks used data-driven models that by nature act as black boxes. The consultants also felt that supervisors often (blindly) imposed the conclusions brought forward by their own data:

> *"If a discrepancy between banks' results was flagged, banks said they were often de facto forced to accept the result of the other bank without a clear explanation or justification of how it was obtained."*

According to the consultants, this shows that banks placed more emphasis on the "importance of being able to explain and understand clearly where results come from" (CFA11), while supervisors seemed more concerned with "…using large amounts of data to make predictions that they deemed more accurate" (CFB2). These competing epistemological logics (explainability vs accuracy) led to misunderstanding and mistrust.

4.2 Rethinking Big Data Driven Decision-Making Accountability and Transparency for Financial Performance

This has significant ramifications for the current accountability mechanisms. According to a bank customer's complaint one of the consultants had read:

> *"Within a split second, all of your results are obliterated and replaced with something completely foreign to you. Additional information is not available upon request. The managers' models are a complete mystery. As a result, making sense of this activity is challenging. It is difficult to comprehend why a portfolio is at risk or where losses are alleged to originate. As a result, I am less concerned with the exercise's outcome. They are not particularly useful to me or my team on an internal level." (CFA5)*

This demonstrates that the banks' analysis results are not always transparent. The results of the stress test have an effect on the supervisory review and evaluation process of a bank (SREP). While both the results of stress tests and the manner in which they are fed into the SREP are opaque, banks frequently express dissatisfaction with the entire process and call for increased transparency. According to another consultant:

> *"Banks, from what I have heard, have appealed the SREP. All I know is that eight banks filed claims in 2014, and four of them were*

successful. Additionally, a law firm in London, England, has recently established itself as a specialist in this field. That, I believe, is perfectly acceptable. Banks are not being arbitrarily bullied, that is certain, but they should be compelled to justify their actions in public. Every individual is accountable for his or her actions, and he must be held accountable for his." (CFA4)

This shift to big data thinking necessitates an important discussion about transparency and accountability. To prevent banks from "gaming" the stress test, "…regulators withheld information about how the results are calculated" (CFB7). Supervisors are increasingly convinced that more data will result in greater understanding and that data can speak for itself. Even when information is not deliberately concealed, "…it is not always obvious how data inputs result in specific outputs during the QA process" (CFA3). Other consultants indicated that they wish to request a justification for other banks policy decisions, such as the SREP given their concerns about the impact it would have on banks' financial performance.

Despite the time constraints of the stress test, the consultants indicated that they attempted to contact the banks for additional information about their results in order to make informed financial and process performance, as well as data-driven decisions. One respondent stated:

"All communication between us consultants and the bank experts has not always been straightforward due to the absence of a direct line of communication. As a result, discussions about the validity and reliability of findings are difficult." (CFB6)

However, several respondents mentioned that discussing the discrepancies in results had "helped them gain a better understanding of risk and improved supervision" (CFA8). In these discussions, consultants stated that banks and regulators were able to be more specific about their methodological choices (and epistemic positions). Joint discussions about the accuracy and validity of the results benefited some, but not all, bank respondents. The consultants also noted, however, that this would be extremely time consuming and unrealistic on a large scale, raising concerns about bias. This shows that data-driven decision making raises critical questions about the appropriate level of transparency and how to justify data-driven decisions in relation to financial and process decisions. The stress test involving big data, were found to be fraught with similar tensions.

4.0 Discussion & Conclusion

Initially, we set out to answer the following research question: "*How can British banks make key financial decisions from knowledge generated by big data to predict financial performance?*" We achieved this by conducting a field study on banking consultants who revealed some insightful information. We present and discuss our key findings of the results.

The use of big data for decision-making has ramifications for predicting financial performance. KM reliability theory has revealed that utilising large data sets for decision-making requires an epistemological foundation, which this paper emphasises: the "epistemology of big data" model (see Figure 1). The contemporary KM reliability concepts of comprehensiveness, disorder and triumph as well as accountability and transparency inspired the epistemological issues posed by big data-driven decision making (Dubnick & Frederickson, 2011). According to the consultants interviewed, the decision-making process is opaque, making it difficult to predict financial performance. Therefore, there is a need to reconsider the utility and necessity of transparency in this era of data-driven decisions.

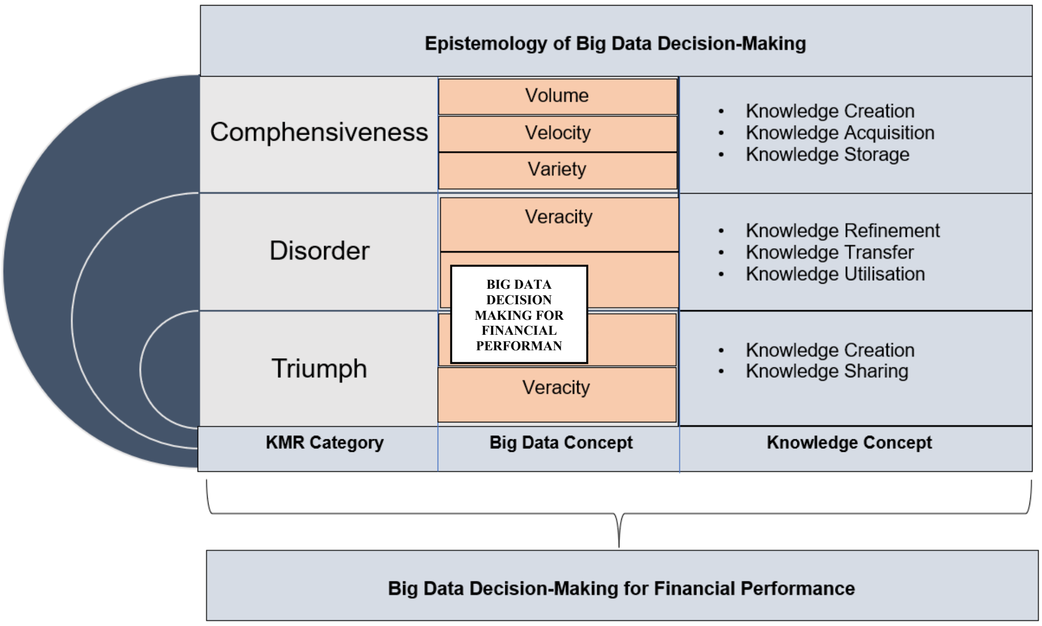

Figure 1. **Epistemological Model of Big Data-Driven Decision-Making for Financial Performance**

The contribution of this paper is derived from the findings which aligned KMR concepts with the idea of big data driven decision making. Our findings indicate that the concept of comprehensiveness (using a large amount of data to provide a comprehensive view of an event's characteristics) is related to the big data concepts of volume, velocity, and variety, as certain amounts of various types of data must be produced in a short period of time to allow banks to make effective financial decisions. The concept of disorder was discovered to be related to the big data concepts of veracity and value, as data must be reliable and of high quality in order to reveal established patterns that can help banks to create value, or in the case of financial decision-making, to improve financial performance. Triumph was discovered to be related to the big data concepts of veracity and volume, as sufficient data models are required to generate high-quality knowledge that is aligned with making the best key financial decisions to improve banks' financial performance.

Based on our findings in relation to accountability and transparency, rather than reducing communication and producing knowledge in silos, banks could approach other banks to collaborate on knowledge production. As a first step, it is critical to acknowledge the participants' divergent perspectives and methodologies. Without this, no meaningful discussion between stakeholders is possible. It is critical for democratic decision-making to be based on information that is agreed upon by both parties, even if it is contested. Accountability is predicated on the justification of the validity of knowledge claims. Along with increasing accountability, relational transparency may also enhance the quality of data control, granted that a wealth of knowledge is produced. Numerous interviews with banking consultations revealed that the (albeit limited) exchange of information and discussions between the banks frequently resulted in improved risk prediction and thus higher regulatory quality, leading to improved financial performance. While most research on how to improve transparency and accountability focuses on alternative methods of disclosing information, this study emphasises the importance of relational transparency by emphasising information exchange rather than information disclosure to predict financial performance (Vedder & Naudts, 2017).

Possessing this information has the potential to have a sizable impact on organisations. When it comes to big data, there is frequently a divide between "believers" and "nonbelievers" in organisations (Loukissas & Pollock, 2017). It should not be a matter of conviction in the production of knowledge, but rather of validity. As Guenduez et al. (2020) point out, there are divergent views on how big data can be used to improve decision-making, in addition to improving financial performance. Chan and Bennett Moses (2017) argue that all stakeholders, particularly regulated entities, should be more involved in order to gain a better understanding of how big data can be used to improve financial decision-making. Policymakers and other stakeholders should establish clear practical and legal standards for the validity of claims about data-driven knowledge in light of the findings in this paper. Stress tests and all decision-making interactions that involve a shift toward a big data mindset and big data analytics are pertinent to this discussion, and thus guidance is needed on how this can or should be accomplished.

The primary limitation of this study was the small sample size, which only captured the experiences, thoughts and opinions of a small group of bank consultants. Although our qualitative study yielded a large dataset of insightful information about big data decision making in the finance context, this only represented a small group of individual perceptions, thus limiting the reliability of the findings. A triangulation of interviews, focus groups and documentation may help to provide more insightful and reliable information.

In conclusion, this paper has provided insight into the epistemological implications of decision-making with large data sets to predict financial performance in British banks. However, we believe there is an urgent need for a broader critical examination of the regulatory implications of the epistemological assumptions associated with the use of big data and algorithms linked to financial performance, and thus future studies could explore this untapped phenomenon.

References

Boyd, D., & Crawford, K. (2012). Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, communication & society*, *15*(5), 662-679.

Chan, J., & Bennett Moses, L. (2016). Is big data challenging criminology?. *Theoretical criminology*, *20*(1), 21-39.

Desouza, K. C., & Jacob, B. (2017). Big data in the public sector: Lessons for practitioners and scholars. *Administration & society*, *49*(7), 1043-1064.

Drisko, J. W., & Maschi, T. (2016). *Content analysis*. Pocket Guides to Social Work R.

Dubnick, M., & Frederickson, H. G. (2011). Public accountability: Performance measurement, the extended state, and the search for trust. *National Academy of Public Administration & The Kettering Foundation*.

Hirschheim, R. (2021). The attack on understanding: How big data and theory have led us astray: A comment on Gary Smith's Data Mining Fool's Gold. *Journal of Information Technology*, *36*(2), 176-183.

Kitchin, R. (2014). Big Data, new epistemologies and paradigm shifts. *Big data & society*, *1*(1), 1-12.

Lepri, B., Oliver, N., Letouzé, E., Pentland, A., & Vinck, P. (2018). Fair, transparent, and accountable algorithmic decision-making processes. *Philosophy & Technology*, *31*(4), 611-627.

Loukissas, Y., & Pollock, A. (2017). After big data failed: The enduring allure of numbers in the wake of the 2016 US election. *Engaging science, technology, and society*, *3*, 16-20.

Manovich, L. (2011). Trending: The promises and the challenges of big social data. *Debates in the digital humanities*, *2*(1), 460-475.

Mayer-Schönberger, V., & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think*. Houghton Mifflin Harcourt.

Mazdeh, M. M., & Hesamamiri, R. (2014). Knowledge management reliability and its impact on organizational performance: An empirical study. *Program*.

O'Malley, M. (2014). Doing what works: Governing in the age of big data. *Public Administration Review*, *74*(5), 555-556.

Redden, J. (2015). Big data as system of knowledge: Investigating Canadian governance. *Compromised Data: From Social Media to Big Data*, 17-39.

Salganik, M. J. (2019). *Bit by bit: Social research in the digital age*. Princeton University Press.

Schwartz-Shea, P., & Yanow, D. (2013). *Interpretive research design: Concepts and processes*. Routledge.

Statista (2022). *Data-driven decision-making in organizations throughout Europe and the United States in 2021*. Retrieved from : https://www.statista.com/statistics/1267733/data-driven-decision-making-corporate-initiatives/ 05/03/22.

Symons, J., & Alvarado, R. (2016). Can we trust Big Data? Applying philosophy of science to software. *Big Data & Society*, *3*(2), 2053951716664747.

Van Dijck, J. (2014). Datafication, dataism and dataveillance: Big Data between scientific paradigm and ideology. *Surveillance & society*, *12*(2), 197-208.

Vedder, A., & Naudts, L. (2017). Accountability for the use of algorithms in a big data environment. *International Review of Law, Computers & Technology*, *31*(2), 206-224.

Wiener, M., Saunders, C. & Marabelli, M. (2020). Big-data business models: A critical literature review and multiperspective research framework. *Journal of Information Technology*, *35*(1), 66-91.

Yeung, K. (2018). Algorithmic regulation: a critical interrogation. *Regulation & Governance*, *12*(4), 505-523.