Organizing for- and in- the Digital Age: A Case of the Indian Banking Industry

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A thesis submitted in partial fulfillment of the requirements for the Doctor of Philosophy degree in Business
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Abstract

For striving and thriving in the digital age, while firms are rushing to digitally transform their organizing practices as well as offerings, scholars are tasked with revisiting the assumptions of extant theories to unpack the phenomenon of organizing for- and in- the digital age. This thesis focuses on distinct facets of this phenomenon. In particular, I examine the firm strategies and work practices of practitioners in Indian banking and financial organizations (Essays 1, 2), as well as the work practices of academic researchers (Essay 3), as they engage with digital technologies.

The first essay elaborates on and tests the theory of discontinuity in trust in money and the resulting spillover effect, through the degree of association with the source of trust discontinuity, on the financial organizations’ ability to capture value through their digital offerings. Using India’s 2016 demonetization as an exogeneous policy shock, organizational-level digital currency transactions as data sources, and regression discontinuity as empirical strategy, this essay documents an unintended consequence of demonetization—value slipping from government- to private- organizations.

The second essay examines the work practices of data scientists as they strive to perform rationality in practice using a qualitative methodology based on observations, interviews, and archival records at three large Indian banks. The study documents the paradoxical tensions faced by the data scientists as they enact the informing practices of inscribing expertise and prescribing insights for rational decision-making in the organizations, and explicates some mechanisms through which the data scientists alleviate those tensions. This study contributes to the emerging literature on data science as a new profession (Part A), as well as offers recommendations for practitioners (Part B).

The third essay examines the work practices of academic researchers using AI-enabled analytical tools. Based on a systematic methodologic review of articles published in IS and management journals, this study documents the prevalent practices of applying topic modeling—namely, the lack of explicit description, contentious justifications, and
polarized, partial, or no validation—that potentially threaten the reliability and validity of academic research. The study proposes a framework to help scholars in mindfully employing algorithmic intelligence in research.

Keywords: digitization, digital currency, data science, machine learning, topic modeling, demonetization, fintech, decision-making, rationality, informing practices, trust, value capture, academic rigor, regression discontinuity design, grounded theory, methodological review
Organizations across industries are increasingly adopting digital technologies in their internal processes as well as in their market offerings. This phenomenon of digitization renders our understanding about organizations’ practices, processes, and strategies inadequate. In this thesis, I examine the effects of digitization on organizations with focus on the firm strategies and practices in the Indian banking industry (Essays 1, 2), as well as the research practices of academic scholars (Essay 3), as they engage with digital technologies.

In the first essay, I examine the impact of India’s 2016 demonetization policy by the government on the ability of banks and other financial organizations to profit from the use of their digital currencies by customers. Using data on various digital currencies and relying on quantitative techniques, I demonstrate that due to the negative impact on Indians’ trust in cash currency, Indians increased the use of digital currencies and preferred those financial organizations which had weaker or no ties with the government (which was responsible for demonetization) due to negative spillover effects.

In the second essay, I examine how data scientists generate insights from (big) data using advanced analytics tools in trying to help organizations adapt to data-driven decision-making. By observing and interviewing data scientists at their workplaces in large banks, I demonstrate the paradoxical nature of choices they need to make in their everyday tasks while using their expertise to generating insights, and prescribing those insights for rational decision-making. I also show some strategies the data scientists adopt to overcome the paradoxical tensions. In addition to theoretical contributions (Part A), I also offer recommendations for practitioners (Part B).

In the third essay, I examine research practices of academic scholars using AI-enabled analytical tools. Based on a systematic methodologic review of articles published in academic journals, this study highlights some potential challenges to the reliability and validity of research due to the prevalent research practices of applying topic modeling, which often lack transparency, provide inadequate justifications, and conduct insufficient
validations of the findings. I propose a framework to help scholars to overcome some of the highlighted challenges in the prevalent practices.
Coauthorship Statement

This thesis includes material that is the result of independent as well as joint research in the form of three original essays. Essay 1 is coauthored with Dr. Jean-Philippe Vergne, Dr. Ning Su, and Mr. Nur Ahmed; Essay 2 (Part A) is a sole-authored paper; Essay 2 (Part B) is coauthored with Dr. Ning Su, Dr. Robert D. Austin, and Mr. Anand Sundaram; Essay 3 is coauthored with Dr. Wendy Günther. In all the essays, I worked as the sole author (Essay 2A), the first author (Essays 1 and 2B), or an equal contributor (Essay 3). As such, I controlled all aspects of the projects including formulating the research questions, conducting the literature reviews, developing the models, performing the analysis, and preparing the manuscripts. I certify that this dissertation, and the research to which it refers, is fully a product of my own work.

Essay 1. I developed this research project as a paper in one of the doctoral courses during my first year in the PhD program. With my first-hand experience of working with two large Indian banks prior to joining the PhD program, and my interest in financial technologies (FinTech) in general, the announcement of the demonetization policy in India naturally attracted my attention, which I developed into a full research project. I wrote the first full draft of the paper, including collecting panel data on digital currency transactions for 46 large Indian banks, developing hypotheses, analyzing data using regression discontinuity design, and writing up the whole manuscript. Having completed the first draft, I invited Dr. Jean-Phillipe Vergne, Dr. Ning Su, and Mr. Nur Ahmed to the project, each of whom brought their specific expertise to it, including theoretical framing and text mining methods. Since then we have revised the paper several times and in each revision, I have played an important and controlling role. The order of authorship – Joshi, Ahmed, Vergne, and Su – accurately reflects our respective contributions. I am currently revising the manuscript for resubmission (1st R&R) at Strategic Management Journal.

Essay 2A. While working on the first essay on the demonetization policy in India, I identified another related, but distinct, theme of increasing adoption of artificial intelligence powered algorithms and the hiring of data scientists with expertise in developing and using these tools by incumbent banks in their quest to become data driven...
in their decision-making. The ideation for Essay 2 started as a term paper in another course during the PhD program, which I subsequently developed into a full research project. Under the guidance of my thesis supervisory committee, I solely handled the complete project including narrowing and focusing on specific phenomenon of data science and analytics in practice, review of extant literature in information systems and organizational theory, identifying research sites and negotiating access, collecting on-site data, iteratively analyzing data and building theory, and writing the paper.

**Essay 2B.** As I was collecting the on-site data for the project, I came across a repetitive theme of rhetoric and myths around advanced analytics tools, like machine learning among data scientists as well as business professionals. My discussions with Mr. Anand Sundaram (a practitioner who heads the data science unit in a bank) during my on-site observations helped in sharpening my understanding about various prevalent myths of data science. In addition to the theoretical implications covered in part A described above, I envisioned a practical relevance of highlighting some of the myths I observed during my study. Accordingly, I discussed this idea of writing a practitioner version of Essay 2 with Dr. Ning Su and Dr. Robert D. Austin. I wrote the first draft of the paper and revised it several times with the guidance of Dr. Su and Dr. Austin. After my preliminary edits, Dr. Su and Dr. Austin also edited the manuscript. Mr. Sundaram worked as our internal reviewer to make sure that we were accurately representing the phenomenon of the rhetoric and reality of data science. The order of authorship – Joshi, Su, Austin, and Sundaram – accurately reflects our respective contributions. The manuscript is accepted for publication at *MIT Sloan Management Review*. Considering the audience of this journal, the manuscript is written in a practitioner-oriented language.

**Essay 3.** While Essay 2 focuses on increased reliance on AI enabled analytics tools in industry, Essay 3 focuses on a similar trend in academic research. While using topic modeling and sentiment analysis in the earlier versions of Essay 1 (not part of the current version), and while observing data science professionals using various machine learning techniques in generating insights from data while working on Essay 2, I realized the importance of the choices the researchers and practitioners alike need to make at each stage of research and analysis, and how such choices are consequential to the outcome
being produced. These were my initial thoughts about Essay 3, which eventually concretized when I met Dr. Wendy Günther (then a PhD student). Dr. Günther had similar observations and experiences in using topic modeling in her own research, so we decided to work together on this research project. Both of us have equally contributed to each aspect of development of the manuscript.
Acknowledgements

My experience during the PhD program at the Ivey Business School, Western University (hereafter, Ivey) has been life-shaping. I have been fortunate enough to be surrounded by many great people who have helped me navigate the journey. I am pleased to take this opportunity to thank (in no specific order) these special people.

First and foremost, I thank the chair of my thesis supervisory committee, Dr. Ning Su, for his unwavering and continued support. Ning has influenced my thoughts ever since we exchanged first emails while I was still working in the banking industry and was contemplating about joining academia. Ning has been a great supervisor in helping me transition from an industry professional to an academic scholar, in guiding me through every aspect of academic research, and yet in providing me enough freedom to explore and carve out my own path. He has been extremely patient with me, showing me the right direction at every juncture of my PhD journey including conceiving project ideas, identifying research sites, collecting and analyzing data, and, most importantly, theorizing. Recognizing teaching as an important skill to develop during the PhD program, Ning also helped me in sharpening my teaching skills by letting me conduct a workshop on Project Management as part of his course.

I am also thankful to my thesis supervisory committee members, Dr. Robert (Rob) D. Austin and Dr. Jean-Philippe (JP) Vergne. Both of them have guided me in learning the art of formulating research questions, building compelling arguments, and writing for an academic as well as a practitioner audience. I developed a deeper understanding about the academic research around financial technologies (FinTech) and was exposed to the community of scholars working in this space with my association with Scotiabank Digital Banking Lab at Ivey and under the guidance of JP. Through his comments and feedback on my essays, JP has always helped me in digging out the most interesting findings and theoretical implications. Similarly, Rob has been extremely helpful in my development as an academician. He has been extremely patient with me and helped me in taking my empirical findings to the level of theoretical arguments. I have learned a great deal of academic writing from Rob and JP while coauthoring papers with them.
Special thanks to Dr. Mark Zbaracki. Mark has been extremely helpful throughout my doctoral studies. My initial interaction with Mark was through the Organizational Theory course, which then translated into a workshop in the form of our continued interaction until today. Thanks to Mark, I developed a deep interest in classic and contemporary organizational theory. On various occasions, Mark has provided me with valuable feedback and advice on my research which included mere research ideas as well as fully developed research papers. Among the several things I learned from Mark are the two most valuable tips, which include explicating the phenomenon of interest fully in the paper before theorizing, especially in the case of inductive qualitative research, and being part of, and building, a community of scholars with similar interests to be successful in academia.

I was extremely fortunate to mark my academic journey under the guidance of the PhD directors at Ivey, especially Dr. Matthew (Matt) Thomson and Dr. Lauren Cipriano. Matt played a vital role in my professionalization in the academic world. The Research Methods course offered by Matt was a great learning experience. Beyond the content of the course, I generally learned the boundaries between ethical and bad science from Matt. The course also helped in socializing with the colleagues from my cohort and learning from each other. Similarly, Lauren has played a significant role in the development of my quantitative skills through her course on Multivariate Analysis. In addition, Lauren has been a great mentor for all the PhD students in general and has brought about several positive changes for the wellbeing of PhD students.

I am thankful to all of the instructors of the courses I took during the course of doctoral studies that exposed me to information systems, strategy, and psychological literature as well as equipped me with the methodological repertoire to conduct my research. Each of them worked as my academic mentors who taught me the content of the course, but also taught me to be a good researcher. These mentors include Dr. Yasser Rahrovani, Dr. Mustapha-Cheikh Ammar, Dr. Adam Fremeth, Dr. Brandon Schaufele, Dr. Ann Peng, Dr. Erin Heerey, and Dr. Andrea Wilson, in addition to Ning, JP, Mark, Matt, and Lauren.

In addition, I would like to thank all my exceptional coauthors who have directly or indirectly contributed to my journey by collaborating on the projects part of the thesis as well as other projects including conference papers: Dr. Wendy Günther, Dr. Saeed Khanagha, Dr. Krsto Pandza, Mr. Nur Ahmed, and Mr. Adam Uhrdin.
I am very grateful to Dr. Derrick Neufeld, who provided me with the opportunity to teach guest lectures in his Data Management courses for MSc and HBA students. Derrick also provided me constructive feedback on both the content and the delivery of my teaching, which helped me develop into a better teacher.

I was very fortunate to be in the company of the vibrant scholars in Information Systems as well as Strategy area groups at Ivey. In addition to the faculty members already mentioned above, I have benefited immensely from the collegial support from Dr. Nicole Haggerty, Dr. Isam Faik, Dr. Warren Richie, Mr. Lameck Osinde, Dr. Lee Watkiss, and Dr. Krista Petit. I also take this opportunity to thank my fellow PhD students in the Information Systems area group, Sampath Bemgal and Esther Gu, who made the journey a lot easier.

I am also thankful to the broader community of scholars beyond Ivey. Over the course of my doctoral studies, these scholars have immensely contributed in making me see this day. Dr. Nicholas Berente, Dr. Martha Feldman, Dr. Ulrike Schultzze, Dr. Emmanuelle Vaast, Dr. Ruthanne Husing, Dr. Arvind Karunakaran, Dr. Anastasia Sergeeva, Dr. Marleen Huisman, Dr. Markos Zachariadis, Dr. Likokw Maruping, Dr. Ioanna Constantiou, Dr. Vern Glaser, Dr. Abayomi Baiyere, Dr. Panos Constantinides, Dr. Samer Faraj, Dr. Silvia Masiero, Dr. Cristina Alaimo, Dr. Shaila Miranda, Dr. Rohit Nishant, Dr Youngjin Yoo, Dr Suprateek Sarker, Dr. Kathy Chudoba, Dr. Marie-Claude Boudreau, and Dr. James Denford are a few of the many scholars who have directly or indirectly helped in building my research portfolio over our innumerable interactions at academic conferences, workshops, and in email exchanges.

Over the course of my doctoral studies, I made several new friends, who of course helped me professionally in shaping my research interests and providing valuable feedback on various occasions, but also helped me personally by making the journey a lot more fun. I thank Vivek Astvansh for showing me the mirror and helping me to critically reflect on my past and future decisions. I thank Andrew Sarta, Ketan Goswami, Nur Ahmed, and Jungsoo Ahn, for helping me filter out the non-interesting ideas. I thank Silvia Masiero, Maheshwar Boodraj, Khadija Vakil, Saurav Chakraborty, Suchit Ahuja, and Arman Sadreddin for making conferences occasions for socialization. I thank Mirit and Igor Grabarski, Fernando and Lucie Naranjo, Sudipendra Nath Roy, Poornima Vinoo, Emal Goswami, Neetu Astvansh, and Amrita Mitra for making me and my family feel at home at Ivey and in the Platts Lane.
neighborhood. I thank Wendy Günther and Marta Stelmaszak for being amazing collaborators.

One of the most important parts of my doctoral studies was the support from PhD and Research office staff. I sincerely thank Paola Ramgren, Carly Vanderheyden, and Katherine Laid for their immense support throughout my journey. They made various administrative elements of research, including maintaining a bio page, claiming expenses, meeting timelines, and applying for Internal Review Board approval, so easy.

I would not been able to start this journey, if Dr. Sarla Achuthan, Dr. C. Gopalkrishnan, and Mr. Ravi Shah had not written the letters of recommendations for my PhD admission. I am also thankful to my ex-colleagues and supervisors from the industry including Mr. Pinal Shal, Mr. Pankaj Popat, Mr. Jignesh Ruparelia, Mr. Sukesh Shastri, and Mr Walter Rodrigues who have helped me at every stage of my career. I express my sincere gratitude to all of them for being my forever mentors.

Finally, I thank my wife, my son, my parents, my sister and her family, my in-laws, my relatives, and my lifelong friends. These are the most important people who have always supported my decisions unconditionally and wished me luck sincerely. Without them, I would not be who I am.
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Chapter 1

1 Introduction

1.1 Digitization, Financial Organizations, and Academic Research

To “survive and thrive in the digital age” (Grover, 2019, p. 25), firms are increasingly compelled to create and capture value by digitally transforming their internal processes as well as availing digital offerings to the consumers. Information systems (IS) researchers (e.g. Bharadwaj et al., 2013; Yeow et al., 2018) as well as organizational scholars (e.g. Adner et al., 2019) have begun to address this trend with studies of firms’ “digital strategy.” With the rapid digitization of everything, scholars have called for revisiting the assumptions of extant theories in IS as well as organizational sciences (Yoo et al., 2010; Yoo et al., 2012). For the IS and organizational scholars, “[t]he question is no longer whether digitization, digitalization, and datafication will change the ways we work, but rather whether our existing theoretical frameworks are equipped to understand, interpret, and even possibly predict the nature of this change” (Leonardi & Treem, 2020, p. 2).

With the increasing intensity of digitization, increasing granularity of digital representation, and increasing intelligent automation, the nature of innovation and the nature of organization are projected to be fundamentally altered (Grover, 2019) and these themes are interconnected. Firms’ digital business strategy includes consideration of digitization of products and services in the form of digital innovations, as well as utilization of information and big data being produced (datafication) from the use of those digital products and services in organizational decision-making (digitalization) to create and capture value (Bhardwaj et al., 2013). I focus on these aspects of digital business strategy that include examination of external consumer facing digital offerings—e.g., debit cards as well as internal workplace digital technologies—e.g., artificial intelligence (AI)-enabled analytics tools (Baptista et al., 2020) in the context of Indian banking and financial industry.

I offer working definitions of the key terms around the phenomenon of digitization that I will use throughout my thesis. At the core of the phenomenon is the concept of
digital, which means information in binary form. Accordingly, “digitization at its very basic level is the conversion of all forms of information (data, video, text, images) to binary form” (Grover, 2019, p. 28). In other words, it is the process through which “key functions and capabilities of industrial-age products including cars, phones, televisions, cameras, and even books” (Yoo et al., 2010, p. 724) can be stored in digital form. Digital artifacts (or technologies) are the artifacts that have these inherent capabilities of storing information in binary form. Such digital artifacts are often considered ambivalent in ontology (Kallinikos et al., 2013) and hence are often identified with the characteristics (in comparison to traditional technology artifacts) that define them (e.g., programmability, generativity, openness). Digital innovation is defined as “the creation of (and consequent change in) market offerings, business processes, or models that result from the use of digital technology” (Nambisan et al., 2017, p. 224). “Digitalization refers to the ways in which social life is organized through and around digital technologies,” and finally “Datafication refers to the practice of taking an activity, behavior, or process and turning it into meaningful data” (Leonardi & Treem, 2020, p. 2).

Financial organizations are at the forefront of this phenomenon. Digital is becoming mainstream in all the areas of banking including payments, retail banking, insurance, wealth management, as well as capital markets and commercial banking (Courbe et al., 2020). This rapid digitization has led to a “FinTech revolution” (Gomber et al., 2018) of the banking and financial services industry that includes the internal workplace technologies as well as the external consumer facing technologies. As defined by Investopedia (2019), “FinTech is used to describe new tech that seeks to improve and automate the delivery and use of financial services.”

In the case of consumer facing digital innovations, digital money (or digital currency) is one of the most relevant innovations to facilitate digitization of economy as it has potential to accelerate virtuality of transactions (Brynjolfsson & McAfee, 2014). “Digital money refers to any means of payment that has cash equivalence but is stored in a purely digital form” (Dodgson et al., 2015). Adoption of such a technology is likely to entail complex interaction among institutions, organizations, and consumers, a transformational phenomenon which calls for extensive research engagement by
management scholars (Dodgson et al., 2015). Digital currency includes electronic currency held in digital accounts as well as cryptocurrency managed directly by users (Hsieh et al., 2018). Financial organizations can create and capture value through digital currencies through two complementary mechanisms. First, they facilitate the transition to branchless banking (Gomber et al., 2018), thereby reducing the overhead costs of facilitating transactions at branches and generating additional revenue in the form of transaction charges. Second, they trigger indirect value creation by facilitating data science projects that rely on transaction-based customer intelligence, which is likely to emerge as the most important driver for value capture for financial organizations (Courbe et al., 2020). Imperatively, it becomes important for financial organizations to make sure that their digital currencies are adopted and used by consumers in order to remain competitive in the market and capture value through their digital innovations. The first essay of my dissertation explicates this phenomenon further by examining the value capture of financial organizations amid the demonetization policy in India (see the section Overview of the Three Essays for details).

Parallelly, financial organizations are also investing heavily in workplace technologies as well as professionals with expertise in such technologies and thereby transforming their internal organization. Among the various generations of workplace technologies, the most recent iterations include the AI enabled analytics tools that operate at the “intelligent augmentation layer” (Baptista et al., 2020, p. 3). Financial organizations like large incumbent banks are well-known for their use of advanced technologies and information in organizing. Banks have been the front runners on adopting these tools in terms of all the waves of analytics evolution (Chen et al., 2012). The recent inclination to adopt and use advanced analytics tools is partly a continuation of this trend and partly also an outcome of the huge piles of data generated out of the digital traces and transactions undertaken by consumers via banks’ customer facing digital offerings. Due to the complex nature of such AI enabled analytics tools, the large incumbent banks have also started hiring professionals with expertise in such technologies, often referred to as data scientists. By establishing separate data science units, these banks endeavor to realize the inherent claims of espoused rationality these AI enabled analytics tools promise to bring in the decision-making processes. However, it
remains to be explored as to how these professionals actually contribute to the rational decision-making processes in the large incumbent banks. The second essay in my thesis explicates this phenomenon further by examining the work practices of data science professionals in three large Indian banks.

Finally, the FinTech and digital revolution is not only transforming the strategy and work practices of business professionals, but also the work practices of academic scholars. Leading universities across the globe have recently started establishing their FinTech as well as Data Science centers and have also started hiring academicians with expertise in multiple disciplines including finance, computer science, statistics, and IS.¹ For instance, the University of Michigan made an announcement in September 2015 about the launch of a $100 million Data Science Initiative. Harvard, MIT, and several other high status institutions have announced similar initiatives and launched undergrad, certification, or graduate programs in data science. This has also resulted in universities hiring candidates with skill in data science to teach these programs as is evident from the announcements made by the universities as well as is reflected in the academic job markets² over the last few years. A subgroup of these scholars typically has expertise in analyzing large volumes of structured and unstructured data using advanced machine learning (ML) tools to generate novel insights and facilitate theory building as well as testing. Yet adoption of such algorithms also comes with its own challenges. “New methods introduce uncertainty in the protocols that need to be followed to source, curate, and analyze data. Consider the application of unsupervised computational methods such as Topic Modeling… whereby researchers need to make decisions” in “sourcing the data... curating the data ... analyzing the data… while a substantial body of work on the application of these techniques has rapidly developed in IS, management, and business …, there can be significant variance in researchers’ choices, the implications of which continue to be explored and understood” (Rai, 2020, p. v). The third essay of my thesis

¹See for example, https://www.finextra.com/pressarticle/80341/amffinance-montreal-donate-2-million-to-set-up-university-fintech-chair
²See for example, As of March 2020, https://www.bu.edu/questrom/faculty-research/faculty-recruitment/
uncovers some of these implications based on a review of prevalent practices of adoption of topic modeling in academic research.

The Indian banking and finance industry as an empirical setting was both a natural and an opportunistic choice. First, the 2016 banknotes demonetization policy which, overnight, removed high value currency notes from circulation presented a unique opportunity to examine the impact of such a massive natural experiment on the financial organizations’ ability to capture value. This was particularly interesting because back then, before the policy implementation, over 90% of India’s economic transactions were still processed in cash currency (Chakravorti, 2016), which is huge for the world’s second most populous country. I was uniquely positioned to examine and unpack this policy shock with my own experience of working with two of the largest private sector Indian banks, which provided me access to conduct formal as well as informal interviews and collect relevant data for the first essay of my thesis. Recently, partly as a consequence of demonetization, India has emerged as one of the leading FinTech economies. Indian consumers are second only to the Chinese in the percentage of online adults who regularly use FinTech functionality. India’s PayTm (a payments wallet turned full function bank) is behind the mobile payment system (PayPay) that has gained the most traction in Japan. The demonetization policy triggered wide scale adoption of digital currencies and also boosted data-rich sectors, such as digital payments in India. India is considered one of the top data science testing grounds because of its demographics, specifically its large numbers of young adults who are using mobile and other technologies. These developments paved the way for my second essay. I noticed that several large incumbent banks had established their own data science units in their quest to achieve rationality in decision-making and in turn create and capture value through data and analytics. Again, with my social and professional network, I managed to obtain access to three large banks for conducting a qualitative study.

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³See, for example, https://www.bloomberg.com/professional/blog/asia-leading-fintech-revolution/.
⁴See, for example, https://www.analyticsinsight.net/countries-which-hold-the-greatest-opportunities-for-data-scientists/).
Overall, my thesis is organized in a multi-essay integrated format. My first essay examines the phenomenon of digital value capture by financial organizations through their digital currency amid the demonetization policy in India using a bank level panel data as well as time series data of digital currency transactions. My second essay qualitatively examines the work practices of data science professionals in their quest to perform rationality in three of India’s largest private sector banks. My third essay examines the prevalent research practices in applying topic modeling in academic research with a focus on the implications of such practices on academic rigor based on a systematic methodological review. Next, I provide a brief overview of each of the three essays.

1.2 Overview of the Three Essays

1.2.1 Essay 1. Digital Value Capture by Financial Organizations following India’s Demonetization

The first essay is a hypothetico-deductive study driven by the phenomenon of India’s demonetization policy. On November 8, 2016, India’s government made a surprise TV announcement that all 500- and 1,000-rupee banknotes would be taken out of circulation four hours later, leaving the country in shock. The stated objective was to “fight against corruption, black money and fake currency” (Anand & Kumar, 2016) by demanding that citizens declare the provenance of their banknotes. Cash removed from circulation, representing 86% of all cash in value, would be returned to the formal financial system and replaced with banknotes equipped with enhanced security features, freshly printed by India’s central bank. The media subsequently referred to this policy shock as “demonetization.” This was a huge shock for the population of financial organizations as well as individual Indian citizens as, back then, over 90% of economic transactions were still processed in cash currency (Chakravorti, 2016).

Leveraging this policy implementation as a natural experiment, the first essay examines the impact on the ability of financial organizations to capture value through their digital offerings. Naturally, adoption of digital currency is a prerequisite for
financial organizations’ ability to capture value created through digital offerings. Such value capture typically stems from fees that organizations charge on digital transactions and from the production of customer data analytics that can subsequently be sold (Amit & Han, 2017; George et al., 2014; Zeng & Glaister, 2018). In India, the financial organizations (e.g., banks) used to be constrained in their ability to capture value from digital offerings due to the low levels of digital currency adoption during the pre-demonetization period, but were now intuitively well poised to capture more value due to demonetization. However, it was not as intuitive in terms of which financial organizations would be able to capture more value and why. This essay answers that question.

To answer the question, I draw on and extend the literature on trust in organizational sociology (Zucker, 1986) and posit demonetization as a discontinuity in Indians’ trust in cash currency. I posit that the trust discontinuity resulted in spillover effects (Jonsson et al., 2009) on associated organizations; hence the organizations that were at arm’s length from the government ended up capturing more value through their digital currency transactions.

I provide causal evidence of my hypotheses by employing regression discontinuity design. I constructed a novel dataset of digital currency transactions in the form of bank level panel data as well as timeseries data from the Indian stock exchange and the local bitcoin exchange, thereby covering several types of organizations in the financial sector, including banks in the payment segment, as well as stock and cryptocurrency exchanges in the investment and savings segment.

This essay makes an important contribution to IS, strategy, and organizational theory literature. It contributes to the IS literature by highlighting the role of social judgments like trust in financial organizations’ ability to capture value through digital innovation, over and above the technology affordances (Autio et al., 2018). It contributes to the strategy literature by highlighting the negative spillover resulting from trust discontinuity as a novel “isolating mechanism” (Rumelt, 1984) that influences firms’ ability to capture value. Finally, it contributes to organizational theory by demonstrating
the characteristic of non-neutrality of currency, which has been largely overlooked in the extant literature.

1.2.2 Essay 2. Data Science and Decision-making in Organizations

The second essay is an inductive theory building study examining the practices of data science professionals in three large Indian banks. It is written in two parts, one for the academic audience and the other for the practitioner audience.

1.2.2.1 Part A. Custodians of Rationality: Inscribing Expertise and Prescribing Insights through Data Science

Regarded as the sexiest job of the 21st century (Davenport & Patil, 2012), over the last decade, data science has attracted considerable attention from academicians and practitioners alike. Data science is considered to be “an interdisciplinary field that combines statistics, data mining, machine learning, and analytics to understand and explain how we can generate analytical insights and prediction models from structured and unstructured big data” (George et al. 2016, p. 1493). Emergence of data science as a profession (Bechky, 2020) around AI-enabled analytics tools (Chen et al., 2012) signifies one of the most recent manifestations of organizations’ quest to pursue intelligence (March, 2006).

For organization theorists and IS scholars alike, it is important to understand how organizations integrate data science professionals into their existing practices and processes, as “beyond … fascination for data scientists, ambiguity has reigned regarding what they do, who they are, and whether their occupation would endure” (Vaast & Pinsonneault, 2020, p. 2). Early studies unpacking the phenomenon of data science, either focused on the “consequences of quantification” (Glaser 2014, p. 3) of decision-making on the work practices of business professionals and domain experts (e.g., Aversa et al., 2018; Bader & Kaiser, 2019) or on the role of quantified representations across knowledge boundaries (Barley, 2015) in the collaboration and coordination between data scientists and business domain experts (e.g., Pachidi et al., 2020). These studies invariably extend our understanding of data science, from the perspective of collaboration.
among data science and business professionals, as well as implications for the work practices of business professionals. However, we still have limited understanding about the work practices of data scientists and their role in business decision-making. In order to extend our understanding in this space, I ask the research question: How do data science professionals enact their informing practices while aiming to facilitate rational decision-making in incumbent organizations?

Building on the literature on rationality in practice (Cabantous & Gond, 2011), information production by knowledge workers (Schultze, 2000), and emerging literature on data science and analytics in practice (Glaser, 2014), I answer this question by conducting a field study of the data science units of three large Indian banks. Based on a qualitative analysis of on-site observations, real-time as well as semi-structured interviews, and archival records, my findings suggest that data science professionals perform rationality by iteratively enacting the informing practices of inscribing their expertise in the models and insights they produce, and prescribing the insights thus produced to the business professionals for the rational decision-making in organizations. The two practices of inscribing the expertise and prescribing the insights are deeply intertwined, and hence create occasions that influence the salient choices being made in the corresponding practices, which at times create paradoxical tensions making them prioritize one practice (e.g., prescribing insights) over the other (e.g., inscribing expertise). The data science professionals at times embrace these paradoxes and find workarounds by triggering the attention of business professionals. The primary contribution of this study is toward the emerging literature on the profession of data science and the practices of quantifying decision-making in organizations.

1.2.2.2 Part B. Rhetoric and Reality of Data Science: Prevalent Myths and Lessons for Practitioners

The scholars in management and IS have long insisted on the importance of relevance and impact, over and above the rigor in academic research (e.g., Barrett & Oborn, 2018; Moeini et al., 2019; Sharma & Bansal, 2019). Two of the most important means through which academic scholars can engage in impactful and relevant research for practitioners
include collaborating and cocreating knowledge with practitioners and writing specifically for the practitioner audience, aiming at practitioner oriented journals (Marabelli & Vaast, 2020). Through this second part of the essay, I endeavor to write for the practitioner audience by collaborating with a practitioner, the overview of which is provided herewith.

Data science as an occupation and data scientists as professionals have increasingly become highly sought after among large corporations (Veeramachaneni, 2016). Incumbent firms in many industries have made significant investments in creating their own data science capabilities, often by establishing their own data science teams. As per the professional code of conduct of the Data Science Association,⁵ a Data Scientist means “a professional who uses scientific methods to liberate and create meaning from raw data.”

As these data scientists seek to apply various advanced analytics tools, often powered by AI and ML, they also contribute to the increasing rhetorical meaning of data science as mere application of AI and ML. The diffusion of management practices (Zbaracki, 1998) as well as new technologies (Howard, 2019) often creates both truths and myths that require demystification, and the diffusion of AI-enabled analytics tools and the emergence of data science are no exceptions; there are several debates among experts about what exactly constitutes data science. However, there is a consensus that around all the hype, there is some ring of truth (Schutt & O’Neil, 2013). For senior managers, it is important to be able to demystify the myths and get to the reality of data science in their endeavors to become data-driven in their decision-making with the help of data scientists (Bean & Davenport, 2019).

In this essay, I report insights based on my research at three large Indian banks (as described in Part A) as well as based on the personal experiences of the practitioner coauthor (see more details under the authorship statement) in the form of five vignettes.

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⁵See for details: https://www.datascienceassn.org/code-of-conduct.html
These vignettes help disentangle some of the myths from reality and provide important lessons for practitioners.

1.2.3 Essay 3. Algorithmic Intelligence in Research: Prevalent Topic Modeling Practices and Implications for Rigor in IS and Management Research

The third essay is a methodological review reflecting on researchers’ practices of using algorithmic intelligence-based techniques in academic research. IS researchers as well as organizational scholars have increasingly started relying on computationally intensive algorithms that involve analysis of structured (traditional) as well as unstructured (non-traditional) large volumes of data—often referred to as big data (Grover et al., 2020). Increasingly, such algorithms are developed in the reference discipline of computer science, and are increasingly powered by AI and ML techniques. I refer to this phenomenon as algorithmic intelligence in research.

The increased reliance on algorithmic intelligence in academic research poses some challenges for academic rigor as highlighted in recent editorials and commentaries in the leading IS journals (e.g., Newell & Marabelli, 2015). Cautioning against big data empiricism, senior scholars have implied that algorithmic intelligence in research may pose challenges to reliability and validity (Johnson et al., 2019) and that the nature of choices made by researchers while employing algorithmic intelligence need to be thoroughly examined (Rai 2020).

This essay unpacks some of these implications with an example of topic modeling—a special class of algorithms utilized in analyzing textual data. In particular, I conduct a methodological review of articles, published in IS and management journals till December 31, 2019, using topic modeling as one of the key methods. The focus in the iterative coding was to look for the hierarchical choices made by researchers while applying topic modeling, the transparency with which the choices are described and justified, the nature of justifications offered, and the practices of validating those choices.
This essay contributes to the emergent stream of literature in IS and management scholarship that employs algorithmic intelligence in research. In particular, the essay highlights the prevalent practices of lack of explicit description; contentious justifications; and polarized, partial, and at times, lack of validations. Taken together, these findings highlight potential challenges threats to the reliability and validity of academic research. I then offer an intendedly open framework to help researchers mindfully evaluate their choices while engaging with algorithmic intelligence in academic research and thereby complement the other influential works in this space (Hannigan et al. 2019; Schmiedel et al., 2019).

1.3 Thesis Structure

This thesis is structured and formatted following the Integrated-Article specifications of Western University’s School of Graduate and Postdoctoral Studies. Chapters 2, 3, 4, and 5 contain Essays 1, 2A, 2B, and 3, respectively. References and appendices are provided separately at the end of each chapter (including this one). In Chapter 6, I provide general conclusions of my thesis, and identify future research avenues.

Since Chapter 2 (Essay 1), Chapter 4 (Essay 2B) and Chapter 5 (Essay 3) were developed as coauthored manuscripts, first person plural pronouns (“we” and “our”) are used in these chapters.

1.4 References


Chapter 2

2 Essay 1. Digital Value Capture by Financial Organizations after India’s Demonetization

2.1 Abstract

This study explores the relationship between trust in money and value capture by financial organizations in the context of India’s 2016 demonetization, a policy shock that created a discontinuity in Indians’ trust in money. We argue that trust is a social judgment that can spill over across organizations, and demonstrate that, after demonetization, the value captured by financial organizations decreases with their degree of association to the source of the trust discontinuity (in our context, government-issued cash currency). Results from our regression discontinuity analyses provide causal evidence of an unintended consequence of demonetization—value slipping from government to private organizations. Our theoretical framework linking trust in money to the organizations that make money trusted paves the way for a broader reappraisal of the role that money plays in business life, particularly in processes involving the generation and transfer of organizational value.

Keywords: trust, digital currency, value capture, social judgment, demonetization

2.2 Introduction

With Internet connectivity becoming ubiquitous, firms are increasingly compelled to capture value through digital offerings. Scholars in strategy (e.g. Adner et al., 2019) and IS (e.g. Bharadwaj et al., 2013) have begun to address this trend with studies of firms’ “digital strategy.” Financial organizations are at the forefront of this phenomenon due to the diffusion of digital currency, which includes electronic currency held in digital accounts as well as cryptocurrency managed directly by users (Hsieh et al., 2018).

The adoption of digital currency is a prerequisite for financial organizations’ ability to capture value created through digital offerings. Such value capture typically stems from fees that organizations charge on digital transactions and from the production of customer data analytics that can subsequently be sold (Amit & Han, 2017; George et al.,
In countries with comparatively low levels of digital currency adoption, financial organizations (e.g., banks) are constrained in their ability to capture value from digital offerings.

As of 2016, in India, the world’s second most populous country, over 90% of economic transactions were still processed in cash currency (Chakravorti, 2016). When on November 8 of that year, India’s government made a surprise TV announcement that all 500- and 1,000-rupee banknotes would be taken out of circulation four hours later, the country was in shock. The stated objective was to “fight against corruption, black money and fake currency” (Anand & Kumar, 2016) by demanding that citizens declare the provenance of their banknotes. Cash removed from circulation, representing 86% of all cash in value, would be returned to the formal financial system and replaced with banknotes equipped with enhanced security features, freshly printed by India’s central bank. The media subsequently referred to this policy shock as “demonetization.”

Demonetization implied replacing, within a few weeks, most existing cash currency with new banknotes; intuitively, this could have created a temporary window of opportunity for the growth of digital alternatives to cash. While an early study of demonetization’s impact, based on partial data, found “no change in the use of digital payment methods and savings [behavior …] one year after implementation of the demonetization” (IFMR Lead, 2018, p. 3), recent economic research based on more exhaustive data concurs that demonetization led to a “permanent increase in the degree of digitization of the economy” (Lahiri, 2020, p. 72; a similar conclusion is reached in Agarwal et al., 2018; Chodorow-Reich et al., 2020; Crouzet et al., 2020). These studies argue that a temporary cash shortage in the weeks immediately following demonetization drove digital adoption in India.6

The demonetization episode leaves us with an unanswered question eminently relevant to strategic management: In the aftermath of the exogenous shock engendered by

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6These studies have a common focus on macroeconomic implications (e.g., GDP growth) and policymaking (e.g., monetary policy) at the country or district level; as a result, strategic implications at the firm level have yet to be explored.
demonetization, which financial organizations captured more value from digital currency adoption, and why? Extant literature has shown that specific resources might increase a firm’s readiness to leverage an opportunity created by an exogenous shock of this magnitude (Makhija, 2003; Wan & Yiu, 2009) and our paper offers a complementarity explanation, grounded in the literature on trust (Poppo et al., 2008) and social judgment spillovers (Yu et al., 2008).

We contend that demonetization marks a distinct break in time that affected trust in cash currency in India; such trust discontinuity resulted in spillover effects on associated organizations. Indeed, qualitative evidence suggests that trust in cash currency was affected by demonetization. Demonetization caused weeks of trouble to hundreds of millions of Indian residents, some of whom feared that such a surprising policy move could be employed again in the future despite a government promise that it would be a one-off tactic (e.g., Dutt, 2016; Zabiliūtė, 2020).

The likelihood of trust spillovers increases in proportion with a bystander organization’s association with the source of the crisis (Jonsson et al., 2009). We thus posit that organizations more closely associated with the government behind the demonetization will be less appealing to potential customers (Durand & Vergne, 2015; Jensen, 2006) after the policy shock. As a result, the value captured by financial organizations from digital adoption following demonetization should decrease with their degree of government association.

Our regression discontinuity analyses provide causal evidence in support of this argument across several types of organizations in the financial sector, including banks in the payment segment, as well as stock and cryptocurrency exchanges in the investment and savings segment. Moreover, we provide evidence that trust is indeed the mechanism driving our findings by showing that, in India’s states where trust in the federal government decreased around the time of demonetization, our hypothesized effect is stronger.

Our study’s primary contribution is to the strategy literature on value capture (Pitelis, 2009). Strategy scholars argue that organizations may not be able to capture the
value they create unless an “isolating mechanism” (Rumelt, 1984)—for instance, a patent—“prevents replication of the value-creating new task, product, or service by a competitor” (Lepak et al., 2007, p. 188). In our context, we find that a trust discontinuity can create such an isolating mechanism, albeit not because the latter prevents replication by competitors. Instead, our findings reveal a complementary mechanism to explain weaker value capture whereby, instead of having competitors pull customer value to themselves through product replication, customer value is pushed in the direction of competitors due to the focal firm’s negatively perceived associations. In other words, we show that in addition to strategic actions (Lieberman et al., 2018), a firm’s ability to capture value also depends on association. This finding suggests that proximity with stakeholders does not only affect value creation (Cabral et al., 2019; Kern & Gospel, 2020) but also value capture. Put simply, trust is an antecedent of value capture.

Our second contribution is to the literature on digitalization and digital adoption. Scholars have argued that firms’ ability to capture value depends on such factors as firm-specific resources (Lokuge et al., 2019), technological literacy, and user experience enabled by digital technology affordances (Autio et al., 2018). If this were the entire story, neither firms’ proximity to the source of demonetization nor Indians’ level of trust in the federal government would explain persistent heterogeneity in digital value capture across financial organizations. Our finding that social judgments of firms (independent of both strategic behavior and the technology) contributed to digital value capture has interesting and important implications for business and society.

Finally, our findings emphasize the need for management scholarship to envision value capture in relation to money—an artifact of civilization that is not only socially constructed (Luhmann, 1979; Simmel, 1907; Zelizer, 1994) but also shaped by the very organizations, public and private, that make money trusted (Harmon, 2019; Spicer & Okhmatovskiy, 2015; Yue, 2015). Complementing demonetization research that showed that the forms of currency used for transacting are not neutral for country-level outcomes such as GDP growth and employment (Chodorow-Reich et al., 2020), our study further demonstrates the non-neutrality of currency for firm-level value capture—namely, a shift from cash to digital currency advantages certain firms independently of their resource
base. By advancing a framework to understand value and currency from an organizational perspective, we are hopeful that management scholarship can, in the future, increase its share of voice around a crucial phenomenon that, in our discipline, has for too long been a blind spot and yet consistently populates media headlines in the age of decentralized cryptocurrency (e.g., Bitcoin, Dai) and firm-sponsored private money (e.g., Facebook’s Libra).

2.3 Setting: The Currency System in India and Demonetization

2.3.1 Demonetization in Context

A currency system refers to the organization of money within a given country. In India, cash currency issued by the central bank has been the country’s prevailing form for exchanging and storing value—money’s two primary functions. Wages are commonly paid in cash and almost half of Indian households hold cash savings in their homes (Chandrasekhar & Ghosh, 2014). In addition, 85% of electronic money stored in bank accounts is converted into cash at ATMs before being spent (Mazzotta et al., 2015).

While there are cultural reasons why cash historically has had Indians’ preference, there are practical reasons too. Relative to digital currency, cash currency is harder to trace and is thus more suitable for transacting in the informal economy; from a merchant’s perspective, getting paid in cash also comes without fees (e.g., paid to payment processors), thereby implying fewer opportunities for financial organizations to capture value from such transactions.

India’s central bank, the Reserve Bank of India (RBI), manages the cash supply and implements monetary policy. By law, RBI has “the power to act as the federal government’s agent in regulating, inspecting, and controlling all banks” (Kozhikode & Li, 2012, p. 341). In practice, RBI has little independence from the government and can be considered a government agency.

On November 8, 2016, the government and RBI’s concerted demonetization aimed at voiding large denomination banknotes to curb corruption, tax evasion, and banknote counterfeiting—all of which could be facilitated using highly anonymous, hard-to-trace
cash currency (by contrast, digital currency transactions are recorded permanently in
digital ledgers, which makes them easier targets of accounting forensics and de-
anonymization).

The Indian population had 50 days to either deposit their demonetized banknotes at
a bank or exchange them for valid banknotes, such as the new 2,000-rupee note with
better security features that the government was rolling out. During a brief transition
period until mid-March 2017, the government imposed daily and weekly restrictions
limiting how much cash could be taken out of bank accounts and ATMs, and required
that large transactions (e.g., for wedding expenses) comply with “know your customer”
regulations. Note bearers needed to prove their identity and explain the source of their
funds, otherwise the cash lost its value. Gradually, 99.3% of the demonetized banknotes
were legally returned to the financial system (The Economic Times 2018), which
suggests that little dirty money in cash currency was flagged for removal from
circulation.

2.3.2 Demonetization as Discontinuity in the Trust Indians Have in
Cash Currency

Many banking sector executives were taken aback (Wilson, 2017) by the demonetization
announcement. For instance, Rana Kapoor, then CEO of YES Bank, described the move
as “shock treatment.” HDFC Bank Chief Executive, Aditya Puri, confirmed that no one
in the banking industry saw it coming—only “a handful of people knew... [the] RBI
chief and very few senior people in government, and that’s it.”

Besides the unexpected and sudden character of the government move, many
concur that demonetization possibly affected the trust that Indians have in cash currency.
Anthropologist Zabiliūtė (2020, p. 73) reports that the event “had stormed India and
shaken people’s perceptions, trust, and engagement with diverse forms of payments.”
Consistent with this account, an Indian journalist submitted that “people may want to
shift to the digital mode of payment now that their trust in cash has been shaken” (Singh,
2016). In an attempt to explain the underlying mechanism, an Indian engineer suggested,
with a touch of irony, that “the implied threat of future demonetization (sorry, turn in
those 2,000 Rupee notes, pink wasn’t a nice [color] after all) would make people hoard cash less,“ thereby essentially “reducing their trust in cash” (Madathil, 2016). Consistent with this, rumors about the possibility of another demonetization (of the new 2,000 Rupee notes) have been floating around ever since the 2016 shock (e.g., ET Online, 2017; Business Standard, 2019; The Indian Wire, 2020). Dhirendra Kumar, CEO of Value Research Online, argues that “cash is risky after demonetization; can’t say what Modi[‘s government] will do next […] People work in cash, earn profits in cash and accumulate wealth in black [money]. So far, this has been effectively a riskless option. This is no longer true—and that's the real change. For the first time, there is real danger and real unpredictability in continuing to do so” (Kumar, 2016).

The above comments touch upon the very definition of trust in the management literature, characterized as the “expectation that the other party can be relied on [and] will behave as predicted” (Zaheer et al., 1998, p. 143). Trust has a “backward-looking aspect” (Puranam & Vanneste, 2009), also referred to as the “shadow of the past,” which influences “expectations of continuity” (Poppo et al., 2008, p. 39). Put simply, this means that a prior breach of people’s expectations fuels suspicion that a similar breach could occur again in the future. By setting a precedent, demonetization represents a distinct break in time that creates a discontinuity in the Indian cash currency’s track record. Given fears that, despite the government’s promise, demonetization may well be implemented again in the future, there are lingering doubts as to whether Indian cash currency can be trusted to “behave in a predictable manner” (Zaheer et al., 1998, p. 143). As neatly summarized by Chakravorti (2016) in his commentary on demonetization, “if there is a shadow of doubt that affects one party’s trust in a particular form of currency, the other will prefer to not rely on it.” We summarize these ideas by referring to demonetization as a discontinuity in the trust Indians have in their cash currency (or in “trust in cash” for short). This discontinuity in trust in cash represents an “environmental jolt” (Wan & Yiu, 2009) exogenous to India’s financial organizations (except RBI, which planned demonetization in secret).7

7Throughout the essay, our arguments concern different forms of currency (cash, electronic, cryptocurrency) within a single national currency system (India’s Rupee). The paper is thus concerned with
Even though digital currency adoption was not initially stated as one of the objectives of demonetization, the fact that trust in cash currency became questioned by some in the aftermath of the shock creates a favorable ground for a potential shift from cash to digital—indeed documented in macroeconomic research (e.g. Chodorow-Reich et al., 2020). The next section develops hypotheses about what this could imply for value capture by India’s financial organizations.

2.4 Trust in Cash and Digital Value Capture: Hypotheses

2.4.1 Baseline Hypothesis: A General Shift from Cash to Digital Currency

Money used to exchange, and store value is differentiated across two primary forms of currency: cash and digital. Within each form, financial organizations, public and private, compete to capture a share of the value created for customers. For instance, central banks primarily issue cash currency to individuals; commercial banks primarily issue electronic currency (e.g., as loans); meanwhile, a new breed of “decentralized autonomous organizations” (Hsieh et al., 2018), such as Bitcoin, primarily issue cryptocurrency through processes known as mining and staking. Since different forms of currency are substitutes for one another and can easily be converted from one form to another, organizational competition emerges both within and between forms to capture value from demand for currency (e.g., when consumers want more digital currency, banks that capture value through account servicing fees compete not only with each other but also with cryptocurrency organizations claiming lower transaction fees than centralized banking).

As some question trust in cash, one may expect a decrease in cash use and a related increase in the use of the alternative form, i.e. digital currency. Since recent economics research has demonstrated a growth in digital currency use following demonetization, we substitute effects between forms of currency within India, not with exchange rate fluctuations between national currencies. We have no reason to believe that a discontinuity in the trust in cash currency within India would have exchange rate implications for the Rupee at an international level. In fact, the Rupee remained quite stable against the U.S. dollar in 2016-17.
state our first prediction as a baseline hypothesis and confidently expect to find evidence corroborating existing accounts (Agarwal et al., 2018; Chodorow-Reich et al., 2020; Crouzet et al., 2020; Lahiri, 2020):

**Baseline Hypothesis.** After demonetization, Indians shift away from transacting in government-issued cash currency, resulting in additional value capture by India’s financial organizations that deal in digital currency.

2.4.2 Which Financial Organizations Capture More Value?

Trust in a particular form of currency, namely the judgment that it constitutes a reliable and predictable medium to exchange and store value, is fundamentally driven by trust in the issuers and custodians of that currency, which are almost always organizations (public, private, or a combination thereof). An opinion widely shared in the financial sector, and summarized by European Central Bank economists, is that “higher levels of trust in the central bank […] promote trust in the currency” (Bergbauer et al., 2020; see also Harmon, 2019). Similarly, to trust electronic currency existing as deposits, one must trust the commercial bank that holds these deposits. When trust in the organization behind the currency goes away, such as in the case of a “bank run” (Yue, 2015), people shift their holdings to a different form of currency, hopefully backed by more trusted organizations (e.g., by withdrawing commercial bank deposits as cash, one essentially shifts one’s trust from a private bank to the central bank). Similarly, trust in the bitcoin cryptocurrency depends on the trust—more decentralized in this case—that one has in the organizations of miners and developers that form the fabric of the Bitcoin community. Put simply, currency can hardly be more trusted than the organizations in charge of its issuance and custody.

In our setting, the discontinuity in trust in cash goes hand in hand with a corresponding discontinuity in trust in the government and central bank (RBI) behind demonetization. The head of an established Indian NGO, for instance, wrote that “since November 8 last year, the Reserve Bank of India (RBI) has been facing a credibility crisis” (Mehta & Kulkarni, 2017). Larry Summers of Harvard University, former director of the National Economic Council for President Obama, called demonetization the “most
sweeping change in currency policy in the world in decades, […] that has resulted in […] loss of trust in the government” (The Indian Express, 2016).

Since organizational trust concerns a “decision or opinion about the social properties of [an] organization,” it can be regarded as a form of “social judgment,” much like legitimacy and reputation (Bitektine, 2011, p. 152). When sudden shocks, such as panics, scandals, or crises happen, social judgments about associated organizations tend to spill over to proximate and similar entities (Barnett & King, 2008; Piazza & Perretti, 2015). In the financial sector more specifically, management scholars have shown that similarity in terms of organizational form (Greve et al., 2016), as well as affiliation to specific actors (Yue, 2015) or governance bodies (Yue et al., 2013), act as conduits for the diffusion of negative social judgments. Piazza and Jourdan (2018, p. 167) argue that “a key mechanism for contamination […] is generalization […]: actors perceived as being similar, and associates, become themselves suspects,” starting with organizations positioned close to the source of a crisis (Jensen, 2006; Yu et al., 2008).

Financial organizations dealing in digital currency (e.g., commercial banks for electronic currency, cryptocurrency organizations) vary in their degree of similarity and in their affiliation to the government and central bank. In India, due to either regulatory reliance or affiliation by way of partial government ownership, financial organizations dealing in digital currency are aligned to various extents with the government organizations at the source of the discontinuity. As per our previous arguments, this degree of association is expected to channel the diffusion of trust spillovers, which suggests qualifying our baseline hypothesis and predicting less additional value captured for financial organizations more strongly associated with the government and RBI:

**Hypothesis (H1).** After demonetization, the additional value captured by financial organizations dealing in digital currency is inversely proportional to their degree of association with the government and central bank.

Trust in cash is intimately related to trust in the organizations that issue cash currency, namely the government and central bank. Presumably, Indians who trust the government more may feel more comfortable with demonetization and, if so, their trust in cash currency would not be affected as much as a result. That India’s primary opposition
party at the time of demonetization opposed and sought to reverse the policy in Parliament lends credence to the idea that those who tended not to trust the ruling government also took issue with the implications of demonetization for cash (e.g., the opposition claimed that demonetization would make the use of cash problematic, which would disproportionately affect the poor; Times of India, 2016).

It follows that financial organizations based in areas experiencing a decrease in trust in the government should be able to capture more digital value after demonetization, due to trust in government-issued cash currency being questioned. Formally:

**Hypothesis (H2).** Banks headquartered in states where trust in the government decreases around demonetization will capture more digital value than banks headquartered in states where trust in the government increases.

### 2.5 Data and Methods

#### 2.5.1 Overview of the Research Design

A regression discontinuity approach enables us to exploit the exogenous variation in trust in cash created by demonetization and relate causally the trust discontinuity to value captured by financial organizations across forms of currency (i.e., cash and digital, with the latter including both electronic and cryptocurrency). Our main panel dataset on 46 Indian banks is structured monthly. We implement a “before–after” design using different time windows (i.e., demonetization ± 5, 6, 7, and 8 months) to assess our findings’ robustness.

A subsequent section examines alternative explanations and further unpacks the mechanisms at play. In an Online Appendix, we provide complementary tests that generalize our findings to the other function of money beyond value transfer (namely, value storage) and to other assets (stocks, gold, bitcoin) that can potentially substitute one of money’s two core functions (e.g. gold can be considered a store of value and bitcoin a means to transfer value). These additional analyses, whose main findings are summarized below in Section 5, are consistent with our hypotheses and further add confidence to the interpretation of the results reported in full here.
2.5.2 Data
The primary digital alternative to cash is, by far, electronic currency stored as account balances tied to electronic payment cards. To track the use of electronic currency, we collected, from the RBI, bank-level panel data on electronic payments made with debit cards at the point of sale (POS). RBI data, which are available monthly for a representative sample of banks, capture transaction volume per electronic card issued. Our data cover 46 banks operating in India and representing over 80% of banking transactions volume. We collected data for bank-level control variables through the Bombay Stock Exchange (BSE), the RBI, and banks’ annual reports and websites. Our data encompass a period of eight months before and after demonetization (sixteen months in total).

2.5.3 Empirical Strategy
Due to temporary ATM restrictions until mid-March 2017, we tested our hypotheses starting from March 2017, five months after demonetization, when Indian consumers could, without any form of government interference, freely choose how to make payments. Our period of observation ended eight months after demonetization, in July 2017, when the government implemented its Goods & Services Tax Bill, another policy that could have affected preferences in money usage.

We used a regression discontinuity design to confirm prior findings that demonetization led to a shift from cash to digital value capture (baseline hypothesis); then, we tested whether financial organizations dealing primarily in digital currency captured more value when they had a weaker association to the government and RBI (H1) and were headquartered in states where trust in the government was decreasing (H2). Regression discontinuity is an established method for causal inference (Hahn et al., 2001; Flammer, 2015; Gelman & Imbens, 2019) that uses a cut-off point to estimate a treatment effect (here, the effect of demonetization).
2.5.4 Dependent Variable

Financial organizations issuing payments in electronic currency capture value by charging fees (e.g., subscription, per transaction, and penalty fees), by holding client deposits in electronic currency (e.g., money custody), and by collecting data on consumer behavior. Accordingly, a standard industry proxy to estimate how much value is captured is the volume of electronic transactions processed (BCG, 2017). In preliminary interviews we conducted with Indian banking executives, references to their bank’s “wallet share” and to being a customer’s “first bank” if the bank’s debit card is used to make most POS payments confirmed the validity of our proxy.8

In line with this industry standard, our main dependent variable, \( value(epayments) \), captures the volume of debit card transactions at POS terminals at the bank level. These transactions are entirely digital and do not involve any cash movement. Since the availability of debit cards in the market constrains the number of POS transactions possible, we computed our dependent variable as the ratio between the volume of POS debit card transactions and the number of debit cards in circulation.

In a stable economy and over a short observation window like ours, any decrease in the proportion of cash transactions should correspond to an increase in digital transactions, since the two forms of currency, cash and digital, are the only two available options. To verify that additional value captured in digital form results, as per our baseline hypothesis, from a decrease in cash transaction volumes, we proxied the latter with bank-level data on \( ATM \) cash transactions volumes. The latter constitutes a reliable proxy given the untraceability of cash transactions (i.e., it is not possible to measure directly the volume of cash changing hands in the informal economy but this volume has

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8Being a native Indian with years of experience in India’s commercial banking sector and having just joined the PhD program (September 2016), I was still well connected with the Indian bankers as well as other business owners and executives who all were impacted by demonetization (November 2016). We conducted a small number of informal interviews as we worked toward the first draft using my former professional network in India’s banking industry to provide additional context and validate the basic premises of this study. Note that, since the start of this research project, none of this paper’s coauthors has had any kind of affiliation (contractual or otherwise) with any of the private or government organizations mentioned here or about which we collected data analyzed in this paper.
to be strongly correlated with the volume of cash taken out of ATMs, since ATMs are the entry points for accessing cash).

### 2.5.5 Independent Variables

For the baseline hypothesis, the independent variable is the *demonetization* treatment, a dummy variable taking a value equal to zero each month up until November 2016 and one thereafter. We first test whether demonetization decreases *ATM cash transactions* before testing whether it increases value captured by banks dealing primarily in electronic currency (i.e., \textit{value(epayments)}).

To test H1, the independent variable captures the degree to which each bank is associated with the government and RBI. Commercial banks in India are equally regulated by RBI but their degree of affiliation with the government varies. Indeed, government ownership in banks ranges from 0% to 95% in our sample (with a mean of 50%). We expect banks with higher government ownership to appear more similar to, and be deemed more closely affiliated with, the government. In line with our theorizing, our independent variable, \textit{degree of government association}, captures the percentage of government-owned shares in 43 Indian banks (we dropped three foreign banks from our sample to avoid foreign government associations confounding our results). For each bank, we collected data on the percentage of shares held by the government from BSE and XBRL filings during the quarter directly preceding demonetization (XBRL India, 2016).

To test H2, we leveraged the federal structure of the Indian political system and collected state-level data on the federal election cycles immediately preceding (in 2014) and following demonetization (in 2019) to observe a potential state-level change in the level of trust voters granted to the government behind demonetization. Many consider demonetization to be the single most significant decision made by the government during their term and Chakravorti (2017), among others, likened the election cycle that followed demonetization to “a referendum on [the government’s] unprecedented action.” While the ruling government replicated its 2014 victory at the country level in 2019, any state-by-state variance can capture local differences in voters’ trust in the government, which
arguably was shaped by demonetization more than by any other policy decision. If the ruling government’s share of votes decreased in a focal state in 2019 (relative to 2014), we treat that decrease as a proxy for focal state voters’ decreasing trust in the government. As per H2, this implies a sharper trust discontinuity experienced locally around demonetization.

2.5.6 Control Variables

We controlled for notes in circulation and inflation using monthly RBI data. Notes in circulation represents the supply of cash. When cash supply is lower, digital currency use is more likely. Inflation represents an increase in the exchange value (price) of goods relative to money, so inflation should be positively related to value capture. Using bank-level panel data collected from the RBI, we also controlled for the number of ATMs and POS terminals (ATM availability could negatively affect electronic currency use by enabling its conversion into cash; POS availability could have the reverse effect by enabling electronic payments). Finally, we also controlled for return on assets (ROA) to account for firm-level performance differences in our tests of H1 and H2. To further capture heterogeneity across firms, we used fixed and random effects for all the models as detailed below. Table 2.1 provides summary statistics.

2.5.7 Modeling & Estimation

Due to the unexpected, country-wide nature of the policy shock, demonetization affected everyone in India, making this event a case of “sharp” regression discontinuity (Imbens & Lemieux, 2008), clearly demarcating the treated units (all financial organizations just before the shock) from control units (all financial organizations just after the shock).

Following Imbens and Lemieux (2008), we used the standard regression discontinuity model to test H1 for bank i in month t:

\[ \text{value(} \text{payment}_i \text{)}_{it} = \alpha + \beta \text{demonetization}_i + \sum_{k=1}^{2} \gamma_k \text{Time}^k_i + \sum_{k=1}^{2} \delta_k \text{Time}^k_i \times \text{demonetization}_i + \gamma_3 V_{it} + \epsilon_{it} \]

\( \alpha \) is the intercept; our coefficient of interest is \( \beta \), which represents the effect of \( \text{demonetization} \) on the dependent variable at the cut-off point; \( \text{Time} \) is the running
variable indicating months before and after demonetization (centered around November 2016); $V$ is the vector of control variables.

In the equation, the third term captures a pre-existing time trend independent of the policy shock, and the fourth term interacts \textit{demonetization} with a polynomial of \textit{Time} to allow for the slope of the trend line to be different before and after the shock. As per the regression discontinuity literature (Akey, 2015; Grembi et al., 2016), we tried fitting our model with linear and quadratic trends and chose the latter based on goodness-of-fit per the adjusted R-Squared statistic. We avoided higher-order polynomials since recent research (Gelman & Imbens, 2019) suggests they are prone to noisy estimates and complicate confidence interval computation.

Our baseline model compares the value captured by commercial banks dealing in electronic currency before and after demonetization to see whether the policy shock had any causal effect. We test H1 by interacting degree of government association $\times$ \textit{demonetization} and H2 by interacting decrease in trust in government $\times$ \textit{demonetization}.

### 2.5.8 Findings

Table 2.2 reports findings obtained for a period ranging from five months before to five months after demonetization (i.e., the bandwidth is $\pm 5$ months). Models tested with bandwidths $\pm 6$, $\pm 7$, and $\pm 8$ months yielded similar results (available from the authors upon request). Variation inflation factors (VIFs) were all below the recommended threshold of 10 (O’Brien, 2007), with an average of 6.45.

Model 1 examines the effect of demonetization on \textit{ATM cash transactions} to assess whether, as per the first half of our baseline hypothesis, Indians shift away from transacting in government-issued cash currency. As predicted, that effect is negative ($\beta = -0.487$, $p = 0.000$). All subsequent models use our bank-level measure of value capture, \textit{value(epayments)}, as the dependent variable. Model 2 includes control and time trend variables. Model 3 completes our test of the baseline hypothesis by showing that banks capture more value in electronic currency after demonetization ($\beta = 0.413$, $p =0.000$)—on average 174% more per debit card issued, relative to pre-demonetization levels. Together,
models 1 and 3 provide strong corroborating evidence for the baseline hypothesis: After demonetization, Indians shift away from transacting in government-issued cash currency (model 1), resulting in additional value capture by India’s financial organizations dealing primarily in digital currency (model 3).

To test H1, we added the interaction of degree of government association × demonetization. A negative coefficient (with a low enough p-value) would indicate support for H1 (namely, the stronger a bank’s government association, the less additional value captured by that bank due to negative trust spillovers). Models testing H1 used random (instead of fixed) effects to avoid having to drop degree of government association from the estimates (this variable varies across firms but not within firms over our 16-month window). Model 4 provides a test of, and support for, H1. The coefficient on the interaction effect is negative and significant (β = -0.236, p = 0.000). To ease interpretation, we plotted this result in Figure 2.1. We also ran our models separately for “public” (model 5a) and “private” (model 5b) banks and found similar support for our hypothesis (Carril et al., 2018).⑨

On average, after demonetization, a bank that is 95%-owned by the government will capture value from an additional 135 digital transactions versus 360 for a fully private bank (monthly, per 1,000 debit cards). Compare, for instance, Indian Bank Ltd (85%-government ownership) with Axis Bank Ltd (16%-government ownership), which generate similar annual revenues per employee (153 versus 148 million rupees). The former saw a small increase in value (epayments) from 270 to 290 (+7.4%), while the latter experienced a massive increase from 590 to 980 (+66.1%).

To test H2, we matched our sampled banks to states, based on the location of bank headquarters. We then added a dummy variable coded as 1 for a given bank when local state voters’ trust in the ruling government decreased between the two election cycles (i.e., lower percentage of votes). Interacting this variable (decrease in trust in the

9 As per the Indian regulator, a bank is “public” if it has over 50% of government ownership, “private” otherwise.
government) with demonetization, we found a positive and significant effect (β = 0.303, p = 0.002) (model 6), indicating a stronger effect of the discontinuity in trust in cash. Banks headquartered where trust in government decreased captured more digital value than their counterparts headquartered where trust in government increased.

2.6 Robustness, Alternative Explanations, and Generalizability

2.6.1 Are the Findings Robust to Assumptions about Functional Forms and Distributions?

We followed best practice (Gelman & Imbens, 2019) in fitting the quadratic model for our estimates, yet model assumptions about variable distribution and functional form could still be influencing our findings. To alleviate this concern, we re-ran all our models using non-parametric tests, which yielded similar results (Imbens & Lemieux, 2008; see Appendix A1 for details).

2.6.2 Can the Findings be Explained by the Rise of Mobile Wallets?

While we captured our dependent variable, value(epayments), based on debit card swipes at POS, mobile wallets represent another way to capture digital value. In India, around the time of demonetization, an India-based mobile wallet company called PayTM had a quasi-monopoly on mobile wallet payments, with close to a 90% market share (Joshi, 2017). The major banks did not offer mobile wallet payments at the time so mobile wallet data would not enable us to test our hypotheses across firms. Still, we tested whether our results were robust to the inclusion of monthly mobile wallet transaction volumes. Findings, available in Appendix A2 (Table A2.1), are similar to the ones reported in this manuscript and in line with our hypotheses.

2.6.3 Trust Discontinuity or a Digitization Trend?

With the rise of India’s digital economy, we expect a secular trend toward digitization, independent of demonetization. To distinguish between this baseline trend and the effect of demonetization, our models included a time trend, consistent with Gelman and Imbens (2019). If the digitization trend alone were responsible for additional value capture with
digital currency, the coefficient of demonetization would not be significant. Figure 2.2 helps visualize the upward digitization time trend pre- and post-demonetization (extrapolated from counterfactual modeling) separately from the causal effect of demonetization on value capture.

We also conducted a placebo test to establish the discontinuity as causally meaningful, as opposed to being a random incident. If it were random, control variables could have experienced a similar discontinuity. We chose number of ATMs as a dependent variable to conduct a placebo test and found no discernible treatment effect (results available in Appendix A1, Table A1.1, Model 3). This shows that demonetization did not result in a disproportionate increase in the number of ATMs, further confirming that the discontinuity caused value(epayments) to increase over and above the digitization trend as proxied by the number of ATMs.

2.6.4 What about Money as a Store of Value?

For individuals and business organizations, money serves a dual purpose: facilitating transactions (e.g., payments) and storing value. Our hypotheses and models have focused on money’s former function and provided evidence of additional value capture by financial organizations that facilitate digital transactions—but what about organizations that facilitate storing value digitally?

Anecdotal evidence suggests that our theory could also hold with respect to the value storage function; for instance, Adhil Shetty, CEO of Bankbazaar.com, noted that, due to the trust discontinuity, “people [should be] looking for a safer asset class […] after the demonetization of big currency notes” (Financial Express, 2017). If our theory holds, we should also be able to observe additional value capture by financial organizations that store value digitally.

Stocks, gold, and the bitcoin cryptocurrency represent the primary non-cash alternatives for storing value. To test our hypotheses in this context, we collected store-of-value data from the BSE and LocalBitcoins.com (see Online Appendix A3). The BSE, India’s largest stock exchange, enables the trading of local stocks and gold in the form of
electronic-traded funds (gold ETFs). LocalBitcoins is one of the largest cryptocurrency exchanges and provides country-specific data. As per our baseline hypothesis, we would expect demonetization to increase the volumes of value stored digitally as stocks, gold, and bitcoin in India. As per H1, we would expect such increases to be larger for value storage alternatives with weaker government affiliation (LocalBitcoins is unregulated by the government and the RBI, unlike the BSE which enables storing value as gold ETFs and stocks). Value capture, in this context, is directly proportional to volumes of currency stored, with several financial organizations benefiting in various ways (e.g., the BSE gains additional listing fees and commissions; brokers and dealers earn more trading commissions; and corporations whose stock is purchased capture additional shareholder value, at least temporarily).

Our findings in Online Appendix A3 show that, post-demonetization, financial organizations facilitating the storage of value in non-cash currency captured more value when their degree of government association was lower, in line with our hypotheses (see Online Appendix A3, Tables A3.1 and A3.2). While for money as means to transact, our models could not include cryptocurrency due to data being unavailable, for money as store of value, we were able to assess value capture in both electronic and cryptocurrency. Furthermore, the inclusion of data on gold and stocks, which are not considered “money,” shows that our theory generalizes to organizations dealing in assets that fulfill at least one of money’s two functions (i.e. gold and stocks are stores of value). Results reported in Online Appendix A3 thus both reinforce and generalize our initial findings.

2.6.5 Could the Effect be Driven by Commercial Banks’ New Value Creation Efforts?

Commercial banks, even though they were unaware of the demonetization plan, may have anticipated the consequences of the trust discontinuity and implemented a light-speed response to the announcement by rolling out new digital infrastructure to create new value for customers (which could enhance digital value capture down the road). One way to do that would have been to push aggressively for the adoption of debit cards (e.g., possibly through consumer subsidies). But our dependent variable, \( \text{value(epayments)} \), is
computed as the number of transactions *per debit card issued*, so the effect we capture in our models is the net of banks’ potential response in this respect. Similarly, banks could have subsidized electronic payments by installing free payment terminals across stores, but our models control for the number of POS terminals installed in the country, so again we capture a net effect beyond the banks’ potential response. More generally, to account for bank-specific strategies, we ran our models with bank-level fixed effects.

Potentially more problematic for causal inference is a possible correlation between a bank’s new value creation potential and its degree of government association—indeed, such a correlation might make our test of H1 difficult to interpret. What if, for instance, banks without government association were more innovative or better positioned to leverage digital currency opportunities, independently of the effect of the trust discontinuity? If this were true, and our bank-level random effects failed to capture such characteristics, we would still find support for H1, though not for the reason we initially conjectured.

To assess this possibility, we divided our sample into two subgroups based on banks’ relative presence in rural/semi-urban areas versus urban/metro areas. Banks with a stronger presence in urban/metro areas may capture more value through electronic payments due to their customers being more digitally savvy and the intensity of interbank competition in urban settings pushing banks to be more efficient and innovative. In other words, banks with stronger urban/metro presence might have a higher potential for digital value creation.

We calculated the *percentage of rural/semi-urban branches* to capture each bank’s relative presence outside large urban centers and split our sample into two subgroups around the median (55%) value. Table 2’s models, 7a and 7b, suggest that banks with higher metro/urban presence captured more value ($\beta = 0.449$, $p=0.000$) following demonetization compared to banks with higher rural/semi-urban presence ($\beta = 0.303$, $p=0.000$). That said, H1 still holds in that stronger government association keeps resulting in lower value capture *in both sub-groups* and to the same extent. In other
words, even after accounting for banks’ value creation potential, government association still negatively affected banks’ digital value capture following demonetization.

2.6.6 Can We Generalize the Arguments Outside the Financial Sector?

The context of money is unique in that it involves financial firms that “specialize in the production of trust;” however, “manufacturing trust is […] not quite like manufacturing steel or soap” since “mechanisms of production have to be socially legitimized before trust can be of more than local applicability, before a real ‘market’ can emerge” (Zucker, 1986, p. 13). In the financial sector, paradoxically, trust is both financial organizations’ product (Zucker, 1986) and a social judgment extended to them (Spicer & Okhmatovskiy, 2015).

The implication is that a discontinuity in trust in a given form of currency can affect the perceived quality of the product being “manufactured,” potentially resulting in demand shifts across forms of currency that affect associated financial organizations. By showing that a shifting pattern of trust can move value from one financial organization to another, our study extends research on the competitive implications of trust discontinuities in the financial sector (Greve & Kim, 2014; Harmon 2019; Haveman & Rao, 1997; Spicer & Okhmatovskiy, 2015; Yue 2015).

However, given the specificities of the financial sector, it is unclear whether, in other sectors, trust in particular forms of currency would covary with trust in specific organizations and whether the latter’s ability to capture value would be affected as a result. An interesting avenue for future research would be to see if this study’s results generalize to organizations that issue digital vouchers acting as quasi-currency, such as loyalty points (e.g., AirMiles) and virtual currencies (e.g., V-Bucks in the videogame Fortnite); or to organizations whose products act, like traditional currencies, as stable stores of value over the long term (e.g., collectible luxury goods, including rare wines and spirits; vintage sports cars; designer houses; and certain types of artwork).
2.7 Discussion and Contributions

By examining the demonetization context, our study extends theory on trust and contributes to the literature on value capture (Lepak et al., 2007; Pitelis, 2009), digitalization (Adner et al., 2019), and the role that money and currency play in the realization of firm value (Greve & Kim, 2014; Spicer & Okhmatovskiy, 2015; Yue, 2015). At an empirical level, our findings corroborate recent work in economics (Agarwal et al., 2018; Chodorow-Reich et al., 2020; Crouzet et al., 2020; Lahiri, 2020) that documented a shift from cash to digital currency in India, with two notable differences. First, our level of analysis is the financial organization and our data are firm-level, not country- or district-level, which generalizes extant evidence and increases its relevance for an audience of strategy scholars. Second, we introduce trust as a mechanism to explain the shift to digital currency, thereby complementing explanations based on forced substitution due to temporary cash shortages (e.g., Chodorow-Reich et al., 2020) and digital network externalities (e.g., Crouzet et al., 2020).10

2.7.1 Trust Spillovers as Isolating Mechanism for Value Capture

Our study’s primary contribution is to the strategy literature on value creation and value capture (Pitelis, 2009). Strategy scholars argue that organizations may not be able to capture the value they create unless an “isolating mechanism” prevents competitors from obtaining and imitating valuable firm-specific assets (Mahoney & Pandian, 1992; Rumelt, 1984). For example, a patent functions as an isolating mechanism to prevent competitors by not only protecting the patented technology but also raising entry barriers for rivals (Somaya, 2003). A common thread among these studies is the focus on firms’ capabilities to restrict imitation by competitors through design choices (Sharapov &

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10 These studies posit that temporary cash shortages are sufficient to explain a permanent shift in favor of digital currency. This could be the case, indeed, if Indians’ preferences for cash were permanently altered by a temporary boost in digital currency adoption. Note, however, that the benefits of using cash relative to digital currency, both for producers in the informal economy (e.g., lower taxes) and for merchants (e.g. lower transaction fees), did not disappear after demonetization. Our trust-based explanation thus potentially provides additional insight into demonetization.
MacAulay, 2020) or based on the legal (Winter, 2000) and economic (Teece, 1986) characteristics of the industry.

We complement this literature by demonstrating that social judgments of trust among consumers play an important role in facilitating value capture. We find that trust spillovers stemming from a discontinuity create an isolating mechanism, albeit not because the latter prevents replication or entry by competitors. Instead, our findings reveal a complementary mechanism to explain weaker value capture whereby, instead of having competitors pull customer value to themselves through product replication, customer value is pushed in the direction of competitors due to the focal firm’s negatively perceived associations. In other words, we show that in addition to strategic actions (Lieberman et al., 2018), a firm’s ability to capture value also depends on association, which suggests that proximity with stakeholders does not only affect value creation (Cabral et al. 2019; Kern & Gospel, 2020), but also value capture.

Our conception of trust spillovers as resulting in the creation of an isolating mechanism is different from Oliver’s (1997:704) “institutional isolating mechanisms,” defined as “barriers to imitation which result from a firm’s reluctance to imitate or acquire resources that are incompatible with the firm’s cultural or political context.” Rather than focus on the firm’s reluctance, our study documents customers’ reluctance fueled by association with the source of a trust discontinuity. Still, similarly to Oliver’s institutional isolating mechanisms, the isolating mechanism documented here is not fully controllable by the focal firm in the short term.

The literature on organizational value (Bowman & Ambrosini, 2000; Lepak et al., 2007), still in its early stages, has emphasized contributions to firms’ value capture (Pitelis, 2009) through innovation (Schumpeter, 1934), managerial resources (Helfat et al., 2009; Penrose, 1959), economies of scale (Chandler, 1962), and strategic positioning (Porter, 1985). By using a quasi-experimental design involving an exogenous discontinuity, we identify shifting patterns of trust as an antecedent of value capture that is independent of these traditional factors.
Pitelis (2009, p. 1119) argued that, “at the [firm] level, […] value created is only realized as value captured,” thereby underscoring the ambiguity of the distinction—often presented as crucial by management scholars but insufficiently understood—between value creation and value capture. Because, in our setting, organizations’ ability to create value is likely unaffected in the short term (e.g., firm capabilities do not change overnight) and consumers’ willingness-to-pay is constant across forms of currency (one Rupee in cash is worth one digital Rupee), we are able to clearly discern value creation from value capture at the firm level—and to identify trust as an antecedent of value capture. Our findings indicate that trust spillovers affecting competitors can suddenly make a focal firm’s offerings more appealing (in relative terms) without the firm having to introduce any innovation. Additional value is thus captured because trust influences consumers’ “subjective valuation” (Bowman & Ambrosini, 2000; Priem, 2007, p. 220) independently of the focal firm’s resources, capabilities, or strategy.

2.7.2 Trust and Digitalization

The literature on value capture through digital technologies focuses on the technical characteristics of the digital offerings in terms of affordances and network externalities (Adner et al., 2019; Bharadwaj et al., 2013). This view is best summarized by Autio et al. (2018), who argue that “digital affordances derive from the technical architecture of digital infrastructures, and they support an economy-wide redesign of value creation, delivery, and capture processes” (p. 74). Based on this logic, digital currencies’ potential lies in disintermediation and generativity. By reducing the power of centralized trust anchors (e.g., banks) in value chains, digital currencies give firms greater freedom to configure their activities to maximize value captured from transactions. The introduction of firm-specific payment systems, in the form of digital apps, by such corporations as Starbucks or Uber, illustrates that possibility. The digitalization of currency also drives generativity, namely, it enables the coordination of geographically dispersed audiences and opens up new ways of harnessing platform momentum without continued input from the platform designer (Nambisan, 2017; Thomas et al., 2014). The digital currency platform Libra, spearheaded by Facebook and whose early design was
forcefully opposed by central banks (Schroeder & Paul, 2019), represents a great example of how to leverage such an affordance for value capture with network effects.

What our study adds to this literature is the notion that trust in the organizations that promote digital currencies plays a powerful role independently of technological affordances. For example, the initial pushback against Libra may have been fueled not only by features of the technical proposal but also by the lack of trust in Facebook Inc—a corporation embroiled, at the time, in scandals involving violations of user privacy, accusations of interference in election processes, and anti-competitive behavior. Indeed, U.S. Democratic senator Sherrod Brown’s anti-Libra arguments did not emphasize the project’s technological affordances as much as the fact that “Facebook has demonstrated through scandal after scandal that it doesn’t deserve our trust” (Schroeder & Paul, 2019). In response, Facebook’s Calibra subsidiary, directly evocative of Libra, was renamed as Novi. As experts noted, “by rebranding Calibra to Novi, Facebook is trying to make it super clear that Libra […] isn’t a Facebook project per se” (Dillet, 2020). Based on this study, we would conjecture that the move will not only benefit Novi but also the organizations associated with it.

The crucial role played by trust in the organizations behind the digitalization of money stems from the intersection of two powerful forces. The first one, as discussed previously, concerns money’s special connection to trust, perhaps best summarized by Zucker’s (1986: 13) claim that the financial sector’s business, ultimately, is “the production of trust.” The second one concerns the platformization of money that results from its digitalization and makes network effects consequential. As money becomes digitalized, it becomes programmable through software, which implies that new services can be built on top in the form of apps (e.g., mobile wallets) and middleware (e.g., blockchain protocols).

Pagani (2013) argued that, within such value networks, the profits and competitive advantages resulting from participation reside dynamically at control points in the network, thereby calling for a network-centric approach to digital strategy (Koch & Windsperger, 2017; Sjödin et al., 2020). However, aside from the digital ties among
organizational participants connected to the same network (e.g., banks connected via SWIFT, merchants connected via PayPal), the more traditional, non-digital networks still influence outcomes in the digital sphere. In our setting, for instance, stock ownership ties between banks and the government, independently of digital network considerations, created trust spillovers that influenced value capture in the digital realm. Similarly, in the Libra example, central banks doubting whether Facebook Inc could be trusted as a corporate actor led to the defection of partners from Libra’s digital network (e.g., Visa, MasterCard, eBay, PayPal).

Our study thus positions trust as the centerpiece bridging the non-digital network of firms’ stakeholders with the digital networks underpinning their online product offerings. Future research should examine how trust effects might spill over from one network to the other, triggering or halting network externalities that contribute to value capture.

2.7.3 Money, Value Capture, and Organizational Competition in the Financial Sector

According to economist Frankel (1977, p. 100), “the free monetary order may serve best to illustrate what it really is: […] the pursuit of trust.” Our findings emphasize the need for management scholarship to envision value capture in relation to both trust and money—an artifact of civilization that is not only socially constructed (Luhmann 1979; Simmel, 1907; Zelizer, 1994) but also shaped by the very organizations, public and private, that make money trusted. In this respect, our study contributes to the nascent management literature on money and the organizations in charge of its issuance and custody (Harmon, 2019; Spicer & Okhmatovskiy, 2015; Yue, 2015).

Far from “undermin[ing] bank accounts [and] the entire economy of trust”, as suggested by Amartya Sen (Dutt, 2016), demonetization instead asymmetrically affected financial organizations, enabling additional value capture by those better positioned in an industry network subject to trust spillovers. The paradox of trust in the financial sector as both an organizational product (Zucker, 1986) and a social judgment depicts a virtuous loop of value capture: The more trust a financial organization is able to produce, the more
it becomes trusted in return, and so on. From this perspective, the literature on bank panics (Yue, 2015) can be reinterpreted as a theorization on how that loop can be disrupted. The spread of rumors can be sufficient to disrupt the loop since trust is a social judgment subject to spillover effects; but rumors are not necessary for panics to occur because trust is also a product whose intrinsic quality can vary, which in itself can be a sufficient impulse to disrupt the loop. Demonetization illustrates the latter scenario.

To maintain trust in money, it is thus crucial to have a high-quality product and to prevent the diffusion of damaging social judgments. This concept is, in essence, what Yue et al. (2013) demonstrated in their study of the New York Clearing House Association (NYCHA). As long as NYCHA, a private regulator, balanced the interests of all affiliated banks, it could mitigate the spread of negative news that amplify bank panics; but when it began to favor elite banks over smaller banks, the latter lost their incentives to protect overall trust in the sector by mitigating the spread of negative judgments amidst crisis. For the same reason, trust at the community level has a direct impact on the forms of currency and the kind of organizational issuers that come to be accepted as alternatives amidst panics (Yue, 2015) since a community’s fabric shapes the diffusion of rumors and other social judgments (Bitektine, 2011).

Money, then, can only standardize social relationships up to a certain point (Simmel, 1907), and in return, these relationships often instill meaning as well as a balancing of private and public interests into money itself. This is essentially what Zelizer (1994) demonstrated at the level of the household and what the present study documents at the organizational level in the financial sector—after emphasizing the need to distinguish between different forms of currency.

2.8 Concluding Remarks

Our study identified a causal relationship between a discontinuity in trust in cash currency and digital value captured by financial organizations, using India’s demonetization in 2016 as an empirical setting. To understand organizational and industry evolution, business scholarship must pay increasing attention to money—particularly, to the government and commercial organizations in charge of its issuance; to
money’s functions, value transfer, and storage, and how these functions relate to organizational value capture; and to the forms of currency, cash and digital, that shape value capture by firms operating simultaneously within digital and non-digital networks. It is time for management scholars to return money to the forefront of our field as a legitimate and crucially important topic of inquiry.

2.9 References


### 2.10 Figures & Tables

![Graph](image_url)

**Figure 2.1: Value Capture and Moderating Effect of Government Association**
Figure 2.2: Digital Value Capture amid Demonetization vs. Baseline Time Trend
Table 2.1: Descriptive Statistics

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<th>Variable</th>
<th>Mean (1)</th>
<th>SD (2)</th>
<th>Min (3)</th>
<th>Max (4)</th>
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<th>(6)</th>
<th>(7)</th>
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Note: (5) is in billions of Indian Rupees
Table 2.2: Hypotheses Testing

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Note: p-values in parentheses
2.11 Appendices

2.11.1 Appendix A1: Non-parametric Tests

Table A1.1 reports results from our non-parametric tests—Model 1 replicates the test of H1 with (a) representing a subgroup of public banks and (b) representing a subgroup of private banks. In both cases, we find that private organizations captured more value relative to public organizations. Similarly, Model 2 provides an alternative test for H2 with (a) representing a subgroup of banks headquartered in states where the ruling party’s share of votes increased in the elections and (b) representing the subgroup of banks headquartered in states where the ruling party’s share of votes decreased in the elections. The coefficients of model 2(a) and 2(b) suggest that firms with headquarters in states where the ruling party lost trust captured significantly more value from demonetization ($\beta_{2b} = 0.083 > \beta_{2a} = 0.045$). Finally, Model 3 represents the placebo test with the number of ATMs as a dependent variable showing no clear effect of demonetization on the number of ATMs, in line with Section 5.3 in the article ($\beta = -89.35, p=0.170$).

2.11.2 Appendix A2: Can Model Findings be Explained by the Rise of Mobile Wallets?

To include mobile wallet transaction volumes as a control, we had to exclude notes in circulation and inflation from the models due to potential multicollinearity concerns (i.e. VIF above 10). Table A2.1 reports our results. Model 1 is the test for H1. The variable of interest, demonetization * degree of government association, is negative ($\beta = -0.237, p=0.000$). Model 2 provides an alternative test of H1 with subgroup analysis, where Model 2a reports findings for the sub-group of public banks and Model 2b for private banks. Our results suggest that private banks captured more relative to public banks ($\beta = 0.245, p = 0.000$ vs. $\beta = 0.054, p = 0.030$). Model 3 is the test for H2. It shows that a decrease in trust in the government is associated with increased value capture ($\beta = 0.303, p = 0.003$). In sum, the results are fully consistent with previous estimates.
2.11.3 Appendix A3: Money as a Store-of-Value

2.11.3.1 Data Collection

We collected store of value data from the Bombay Stock Exchange (BSE) and LocalBitcoins. The BSE is India’s largest stock exchange for trading stocks and gold in the form of electronically traded funds (gold ETFs). LocalBitcoins (https://localbitcoins.com) provides country-specific data, and is one of the largest peer-to-peer bitcoin exchanges globally. At the time of demonetization, bitcoin was by far the most popular, valuable, and accessible cryptocurrency (representing 85% of the total cryptocurrency industry’s market capitalization in late November 2016). Together, Indian stocks, gold ETFs, and bitcoin provide good proxies for alternative stores of value (in lieu of cash), which led us to collect daily trading volume data for each, for the period of demonetization ±12 weeks.

If Indians who previously stored cash at home did not perceive a trust discontinuity, they would deposit their cash in a bank account (and either leave it there or take it out again as cash in March 2017); but if demonetization represented a discontinuity in trust in cash currency, then as per baseline hypothesis, trading volumes for Indian stocks, gold, and bitcoin should increase as publicly listed Indian corporations, India-based gold custodians, and LocalBitcoins operators capture additional value above and beyond the trend line. As per H1, the organizations poised to capture more value from the shift away from cash should be LocalBitcoins; unlike gold custodians or the BSE and its publicly listed corporations, LocalBitcoins (and the decentralized bitcoin organization) are not affiliated or regulated by the government and the RBI. They have no ownership ties to the latter and, as peer-to-peer community organizations, are dissimilar to how the government and the RBI operate.11

11Unlike for money as means to transfer value, where we had a clear measure of the degree of government association with each bank, no quantitative measure is available to capture the government association with cryptocurrency organizations. However, we could contrast the BSE (which handles stock and gold trading) and LocalBitcoins qualitatively. The BSE is highly regulated by the Indian government, and in fact operated as a branch of the government until 2005, when it was finally incorporated as a limited liability
2.11.3.2 Modeling and Estimation

Since we use daily time-series data, the cut-off point is the day of demonetization (November 8, 2016) instead of the whole month. To test the baseline hypothesis, we used a time-series variant of the paper’s regression discontinuity design where the three dependent variables denote, respectively, the trading volume of gold, stocks, and bitcoin on day t.

To test H1, we used the same model as for the baseline hypothesis with bitcoin trading as a dependent variable but included gold and stock trading as control variables. A positive coefficient for demonetization would indicate that demonetization boosts value storage in cryptocurrency above and beyond the increase in gold and stock storage, thereby indicating more value capture around cryptocurrency (e.g., Bitcoin organization stakeholders, such as miners, would capture more in processing fees from the increased volume).12

2.11.3.3 Dependent Variables

Each of the three dependent variables—value(GoldTrading), value(StockTrading), and value(BitcoinTrading)—captures an alternative store of (non-cash) currency. Gold has a long standing as an alternative store of value for the Indian population, and the variable value(GoldTrading) captures the aggregate trading volume for gold purchased digitally through ETFs in India. We collected data on all the Gold ETFs active on the day of demonetization and traded on the BSE.

---

12Note that we cannot re-test H2 in this context since we only have two financial organizations (BSE and LocalBitcoin), both headquartered in Mumbai, leaving us with no variance.
For Indian citizens with non-trivial savings, the purchase of stocks represents the primary way to store value using electronic currency (e.g., on trading accounts and within pension plans). The variable value(StockTrading) captures the trading of India-based stocks. Data for stocks were also obtained from the BSE and represent the total volume of stocks traded on the day of demonetization.

Finally, cryptocurrency represents an innovative alternative to storing value independently of government and central banks. The variable value(BitcoinTrading) captures the volume of bitcoins traded in India, using data from LocalBitcoins.

### 2.11.3.4 Control Variables

In addition to notes in circulation and inflation, we control for day-to-day changes in the price of gold, stocks (using the Sensex index, similar to the Dow Jones in the United States), or bitcoin, depending on the model. All price changes from $t$ to $t + 1$ are measured in percentages and are likely to be important predictors of trading volumes. In addition, we control for trading trends outside of India using trading volumes for global gold ETFs, stocks trading volume on the London Stock Exchange, and bitcoin trading volume in the rest of the world (i.e., everywhere except India). These control variables help us account for global trends influencing local trading volumes and hence facilitate teasing out the local impact of demonetization.

### 2.11.3.5 Findings

Table A3.1 provides descriptive statistics, and Table A3.2 reports models that test our hypotheses over the period of demonetization ±8 weeks. Models 1–6 provide tests for the baseline hypothesis (1–2 for gold; 3–4 for stocks; 5–6 for bitcoin) and Model 7 tests H1. Variation inflation factors (VIFs) were all below the recommended threshold of 10.

First, we test the baseline hypothesis for each dependent variable, where the first model is control model, and the second model is the full model with demonetization introduced. We find that demonetization increases all three volumes, however, the effect is more pronounced for bitcoin in Model 6 ($\beta = 1.071, p = 0.000$). This latter increase,
caused by demonetization, represents 1.07 million rupees, corresponding to a 56% increase over pre-demonetization levels.

In Model 7, we find that demonetization significantly increases bitcoin trading volume ($\beta = 1.261, p = 0.000$) even after controlling for the other two alternatives, i.e., gold and stock trading. These results support H1: following demonetization, as Indians increased their reliance on alternatives to government-backed cash currency for storing value, alternative financial organizations with a weaker association with the government captured more value.

These supplementary analyses provide evidence that our theory generalizes, both to money’s function as a store of value and to organizations dealing in assets that are not considered money (stocks, gold, bitcoin) yet can substitute money’s value storage function. Overall, these findings reinforce confidence in and generalize the manuscript’s main results.

2.11.4 Appendix Tables

Table A1.1: Hypotheses Tests with Non-parametric Models

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>value(epayments)</th>
<th># ATMs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Demonetization</td>
<td>0.023 (0.003)</td>
<td>0.045 (0.021)</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>260</td>
<td>170</td>
</tr>
</tbody>
</table>

Note: p-values in parentheses
Table A2.1: Hypothesis Testing with Mobile Wallet Transactions as Control

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th></th>
<th></th>
<th>value(epayments)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Demonetization</td>
<td>0.249</td>
<td>0.054</td>
<td>0.245</td>
<td>0.181</td>
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<tr>
<td>(0.000)</td>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Demonetization *</td>
<td>-0.237</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degree of Govt Asso.</td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demonetization *</td>
<td></td>
<td></td>
<td></td>
<td>0.303</td>
</tr>
<tr>
<td>Decrease in Trust in Govt</td>
<td>(0.003)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time * Demonetization</td>
<td>0.001</td>
<td>0.025</td>
<td>-0.033</td>
<td>-0.016</td>
</tr>
<tr>
<td>(0.963)</td>
<td></td>
<td>(0.327)</td>
<td>(0.607)</td>
<td>(0.759)</td>
</tr>
<tr>
<td>Time² * Demonetization</td>
<td>-0.004</td>
<td>-0.005</td>
<td>-0.005</td>
<td>-0.001</td>
</tr>
<tr>
<td>(0.421)</td>
<td></td>
<td>(0.294)</td>
<td>(0.680)</td>
<td>(0.866)</td>
</tr>
<tr>
<td>Degree of Govt Asso.</td>
<td>-0.070</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>(0.356)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Decrease in Trust in Govt</td>
<td></td>
<td></td>
<td></td>
<td>0.017</td>
</tr>
<tr>
<td>Time</td>
<td>-0.061</td>
<td>-0.044</td>
<td>-0.087</td>
<td>-0.069</td>
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<tr>
<td>(0.000)</td>
<td></td>
<td>(0.000)</td>
<td>(0.008)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Time²</td>
<td>-0.009</td>
<td>-0.006</td>
<td>-0.012</td>
<td>-0.010</td>
</tr>
<tr>
<td>(0.017)</td>
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<td>(0.025)</td>
<td>(0.092)</td>
<td>(0.092)</td>
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<td>Mobile Wallets</td>
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<td>0.005</td>
<td>0.003</td>
</tr>
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<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Number of ATMs</td>
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<td>-0.000</td>
<td>-0.000</td>
</tr>
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<td>(0.820)</td>
<td>(0.183)</td>
<td>(0.053)</td>
</tr>
<tr>
<td>Number of POS</td>
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<td>0.000</td>
<td>0.000</td>
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<tr>
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<td></td>
<td>(0.193)</td>
<td>(0.000)</td>
<td>(0.002)</td>
</tr>
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<td>ROA</td>
<td>0.103</td>
<td>-0.004</td>
<td>0.155</td>
<td>0.290</td>
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<td>(0.001)</td>
<td></td>
<td>(0.829)</td>
<td>(0.011)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.112</td>
<td>-0.113</td>
<td>-0.295</td>
<td>-0.131</td>
</tr>
<tr>
<td>(0.063)</td>
<td></td>
<td>(0.000)</td>
<td>(0.004)</td>
<td>(0.159)</td>
</tr>
<tr>
<td>Fixed/Random Effects</td>
<td>Random</td>
<td>Random</td>
<td>Random</td>
<td>Random</td>
</tr>
<tr>
<td>Observations</td>
<td>430</td>
<td>260</td>
<td>170</td>
<td>420</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.739</td>
<td>0.728</td>
<td>0.789</td>
<td>0.537</td>
</tr>
</tbody>
</table>

Note: p-values in parentheses
Table A3.1: Descriptive Statistics for Money as Store-of-Value

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Notes in Circulation</td>
<td>13,898.87</td>
<td>3,735.49</td>
<td>8,734.02</td>
<td>17,644.51</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) Inflation</td>
<td>3.13</td>
<td>1.13</td>
<td>1.86</td>
<td>5.30</td>
<td>0.77</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3) value(GoldTrading)</td>
<td>6.56</td>
<td>5.48</td>
<td>2.40</td>
<td>41.17</td>
<td>0.28</td>
<td>0.07</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4) value(StockTrading)</td>
<td>314.19</td>
<td>68.51</td>
<td>185.65</td>
<td>617.22</td>
<td>0.43</td>
<td>0.24</td>
<td>0.32</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>(5) value(BitcoinTrading)</td>
<td>2.38</td>
<td>0.92</td>
<td>1.02</td>
<td>5.37</td>
<td>-0.61</td>
<td>-0.55</td>
<td>-0.24</td>
<td>-0.23</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(6) world Gold ETF</td>
<td>6,127.58</td>
<td>473.85</td>
<td>5,300.00</td>
<td>6,720.00</td>
<td>0.96</td>
<td>0.81</td>
<td>0.21</td>
<td>0.44</td>
<td>-0.54</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(7) Δ Gold Price (t-1)</td>
<td>-0.001</td>
<td>0.01</td>
<td>-0.02</td>
<td>0.06</td>
<td>-0.01</td>
<td>-0.04</td>
<td>-0.08</td>
<td>-0.01</td>
<td>-0.03</td>
<td>0.02</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>(8) LSE Trading Volume</td>
<td>423.63</td>
<td>110.53</td>
<td>123.00</td>
<td>827.00</td>
<td>0.07</td>
<td>-0.16</td>
<td>0.12</td>
<td>0.25</td>
<td>-0.09</td>
<td>0.03</td>
<td>0.13</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(9) Δ Sensex Index (t-1)</td>
<td>0.0001</td>
<td>0.01</td>
<td>-0.03</td>
<td>0.02</td>
<td>-0.15</td>
<td>-0.04</td>
<td>-0.06</td>
<td>0.04</td>
<td>0.13</td>
<td>-0.12</td>
<td>0.02</td>
<td>0.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(10) Δ Bitcoin Price (t-1)</td>
<td>0.01</td>
<td>0.03</td>
<td>-0.09</td>
<td>0.09</td>
<td>0.03</td>
<td>-0.05</td>
<td>0.19</td>
<td>0.00</td>
<td>-0.08</td>
<td>-0.01</td>
<td>0.06</td>
<td>-0.10</td>
<td>-0.12</td>
<td></td>
</tr>
<tr>
<td>(11) value(BTCTrading)(ROW)</td>
<td>195.05</td>
<td>31.83</td>
<td>118.43</td>
<td>248.73</td>
<td>-0.78</td>
<td>-0.79</td>
<td>-0.11</td>
<td>-0.35</td>
<td>0.51</td>
<td>-0.78</td>
<td>0.04</td>
<td>0.01</td>
<td>-0.02</td>
<td>0.09</td>
</tr>
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</table>

Note: (1),(6),(8) are in billions; (3),(4),(11) are in millions of Indian Rupees
Table A3.2: Hypothesis Testing: Money as Store-of-Value

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>value (GoldTrading)</th>
<th>value (StockTrading)</th>
<th>value (BitcoinTrading)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Demonetization</td>
<td>5.393</td>
<td>70.872</td>
<td>1.071</td>
</tr>
<tr>
<td></td>
<td>(0.539)</td>
<td>(0.337)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Time * Demonetization</td>
<td>0.161</td>
<td>-7.698</td>
<td>-0.689</td>
</tr>
<tr>
<td></td>
<td>(0.934)</td>
<td>(0.472)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Time^2 * Demonetization</td>
<td>-0.000</td>
<td>0.262</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(0.927)</td>
<td>(0.004)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Time</td>
<td>0.342</td>
<td>1.980</td>
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<tr>
<td></td>
<td>(0.053)</td>
<td>(0.026)</td>
<td>(0.727)</td>
</tr>
<tr>
<td>Time^2</td>
<td>-0.001</td>
<td>0.050</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.388)</td>
<td>(0.992)</td>
<td>(0.992)</td>
</tr>
<tr>
<td>Δ Gold Price</td>
<td>-87.502</td>
<td>-90.629</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
<td>(0.000)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>World Gold ETF</td>
<td>-0.002</td>
<td>-0.002</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(0.790)</td>
<td>(0.892)</td>
<td>(0.011)</td>
</tr>
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<td>Δ Sensex Index</td>
<td>124.040</td>
<td>136.057</td>
<td>0.124</td>
</tr>
<tr>
<td></td>
<td>(0.927)</td>
<td>(0.894)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>LSE Trading Volume</td>
<td>0.144</td>
<td>0.124</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Δ BTC Price</td>
<td>0.229</td>
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<td>-0.162</td>
</tr>
<tr>
<td>value(BTCTrading)(ROW)</td>
<td>0.000</td>
<td>0.002</td>
<td>0.003</td>
</tr>
<tr>
<td>Notes in Circulation</td>
<td>0.002</td>
<td>0.002</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.000)</td>
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<tr>
<td>Inflation</td>
<td>5.266</td>
<td>12.823</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(0.381)</td>
<td>(0.987)</td>
<td>(0.983)</td>
</tr>
<tr>
<td>value(GoldTrading)</td>
<td>-0.015</td>
<td></td>
<td></td>
</tr>
<tr>
<td>value(StockTrading)</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-20.985</td>
<td>95.271</td>
<td>18.897</td>
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<tr>
<td></td>
<td>(0.363)</td>
<td>(0.774)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Observations</td>
<td>80</td>
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<td>80</td>
</tr>
</tbody>
</table>

Adjusted R^2 0.165 0.197 0.435 0.458 0.282 0.484 0.507

Note: p-values in parentheses
Chapter 3

3 Essay 2A. Custodians of Rationality: Inscribing Expertise and Prescribing Insights through Data Science

3.1 Abstract

Over the last decade, data science has emerged as a new profession that has a promising proposition for the organizations perpetually pursuing rationality. Yet, beyond some discrete studies around how data science techniques might help in increasing descriptive and predictive power of decisions, our understanding about what data scientists actually do in practice has remained limited. Early studies have focused either on the consequences of quantification enabled by data science or the coordination among data science and incumbent business professionals, focusing less on the work practices of data scientists. In this study, I examine the informing practices of data science professionals as they aim to facilitate rational decision-making in incumbent firms. In particular, I report findings from a qualitative study utilizing on-site observations, interviews, and archival records from data science units in three large Indian banks. My findings reveal some paradoxical tensions faced by data science professionals while enacting the informing practices of inscribing expertise and prescribing insights for rational decision-making. I also report some mechanisms that data science professionals adopt in working around these paradoxical tensions. My study contributes to the emerging literature on data science and analytics in practice, and also provides new directions for the extant literature on technologies of rationality in practice, and decision-making in organizations.

Keywords: Data Science, Informing Practices, Rationality, Decision-making

3.2 Introduction

It is “impossible to open a popular publication today, … and not run into a reference to data science, analytics, big data, or some combination thereof” (Agarwal & Dhar, 2014, p. 443). Data science is considered to be “an interdisciplinary field that combines statistics, data mining, machine learning, and analytics to understand and explain how we
can generate analytical insights and prediction models from structured and unstructured big data” (George et al., 2016, p. 1493). Emergence of data science as a profession (Beckky, 2020) around AI-enabled analytics tools (Chen et al., 2012) signifies one of the most recent manifestations of organizations’ quest to pursue intelligence by adopting “technologies of rationality,” as the “pursuit of intelligence in organizations … has increasingly become the responsibility of people with special competencies” (March, 2006, p. 201). In other words, acting as “rationality prescriptors” (Cabantous & Gond, 2011, p. 579), data scientists orchestrate quantification of decision-making processes in organizations (Glaser, 2014).

Regarded as the sexiest job of the 21st century (Davenport & Patil, 2012), over the last decade, data science has attracted considerable attention from academicians and practitioners alike. Several universities have recently started their data science programs and curriculums. For instance, University of Michigan made an announcement in September 2015 about the launch of a $100 million Data Science Initiative. Harvard, MIT, and several other high-status institutions have announced similar initiatives. Parallelly, the demand for data scientists has increased in the industry as well, where not only technology firms, but the firms in other incumbent industries have also started recruiting data scientists in their quest to become data-driven in decision-making.

Yet, “beyond this fascination for data scientists, ambiguity has reigned regarding what they do, who they are, and whether their occupation would endure” (Vaast & Pinsonneault, 2020, p. 2). Several elements of the increasing prominence of data science seem more rhetorical than real. Some experts suggest data science to be a simple relabeling of statistics or computer science, while others consider it to be a child of several fields including statistics and computer science (Blei & Smyth, 2017; Donoho, 2017). Yet, some experts believe that “around all the hype […] there is a ring of truth: this is something new” (Schutt & O’Neil, 2013, p. 4). Especially, there is a belief that organizations that set up all new data science units (instead of rebranding their existing units) by hiring professionally trained data scientists, might be in a position to realize the espoused futuristic image of data analysis as envisioned by Tukey (1962). For organization theorists and IS scholars alike, it is important to understand how
organizations actually integrate these new professionals into their existing practices and processes.

Early studies unpacking the phenomenon of data science, either focused on the “consequences of quantification” (Glaser 2014, p. 3) of decision-making on the work practices of business professionals and domain experts (e.g., Aversa et al., 2018; Bader & Kaiser, 2019; Lebovitz, 2019) or on the role of quantified representations across knowledge boundaries (Barley, 2015) in the collaboration and coordination between data scientists and business domain experts (e.g., Pachidi et al., 2020). These studies take various technology tools-in-use (e.g., AI-enabled analytics tools) as a starting point of their inquiry and examine the selection, application, and outcomes of the tools (Jarzabkowski & Kaplan, 2015), paying less attention to the crucial work of the producers of information, the data scientists. These studies invariably extend our understanding of data science, from the perspective of collaboration among data science and business professionals, as well as implications for the work practices of business professionals. However, we still have limited understanding about the work practices of data scientists and their role in business decision-making. In order to extend our understanding in this space, I ask the research question: How do data science professionals enact their informing practices while aiming to facilitate rational decision-making in incumbent organizations?

It is important to understand the work practices of data science professionals as they perform rationality in practice for several reasons. First, focusing on the tools and technologies at “discrete level,” many of the studies in extant literature attempt to explain “how managers can make better decisions once they have better data and analytic tools … [A]n implicit assumption … has been that” organizations “can capture value while continuing to function as before” (Sharma et al., 2014, p. 434). In such a view of data science treating the analytical models as plug-and-play technologies of rationality, “there do not appear to be any humans,” as data science is treated “as a rational data-driven process of discovery that reveals the underlying nature of a domain” (Muller et al., 2019, p. 1). However, several large organizations in the incumbent industries do develop their in-house AI-enabled analytics models by availing expertise of data scientists. Second,
work practices of data scientists are likely to be influenced by the anticipatory performativity of the models they are supposed to produce to be consumed by business decision makers (Barley, 2015). Yet, we have limited understanding on how such anticipation might influence the nature of rationality in data science work practices. Third, even though we have some visibility about data scientists’ work practices when they function as external consultants or professional service providers (e.g., Glaser, 2014), their practices are likely to differ when they produce inhouse models and function as internal consultants (e.g., Schultze, 2000) within the same organization where the models are being consumed. In sum, it is imperative to examine how data science professionals, acting as “rationality prescriptors,” enact informing practices in an intra-organizational context (Cabantous & Gond, 2011).

In this study, I complement the emerging literature on data science and analytics in practice (Glaser, 2014; Pachidi et al., 2020; Steele, 2016) by examining the work practices of data scientists as they perform rationality (Cabantous & Gond, 2011). I do so by using the concept of information production or informing practices (Schultze, 2000) as an analytical lens. As opposed to the information processing perspective, which mainly focuses on the processing of readily available information by decision-makers (e.g., Turner & Makhija, 2012), the information production perspective allows to examine the workflow of information as it is produced and transformed during the task performance of the experts (e.g., analysts). In fact, the information production perspective complements the information processing perspective by bringing the process of information production and the agents who produce the information into the dynamics of organizational decision-making. I draw on the influential studies of information production in adjacent occupations, including bureaucratic analysts in policy making (Feldman, 1989) as well as intelligence analysts in organizational decision-making (Langley, 1989; Schultze, 2000), in examining the work practices of data science professionals.

To explore how data science professionals perform rationality in practice, I present a field study of the data science units of three large Indian banks. Based on a qualitative analysis of on-site observations, real-time as well as semi-structured interviews, and
archival records, my findings suggest that data science professionals perform rationality by iteratively enacting the informing practices of *inscribing their expertise* in the models and insights they produce, and *prescribing the insights* thus produced to the business professionals for the rational decision-making in organizations. The two practices of inscribing the expertise and prescribing the insights are deeply intertwined, and hence create occasions that influence the salient choices being made in the corresponding practices, which at times create paradoxical tensions making them prioritize one practice (e.g., prescribing insights) over the other (e.g., inscribing expertise). The data science professionals at times embrace these paradoxes and find work arounds by triggering the attention of business professionals. The primary contribution of this study is toward the emerging literature on the profession of data science and the practices of quantifying decision-making in organizations. The study also provides new directions for the literature on technologies of rationality and organizational decision-making.

3.3 Theoretical Background

The focus of this study is on the phenomenon of *data science and analytics in practice*. It is closely related to the literature and discourse on the promise that AI and data science can improve the predictive and descriptive power of decision-making. Yet, for AI-enabled tools to actually influence decision-making in practice, the organizations first need to facilitate the production of information (or insights) that can actually be consumed in decision-making. Accordingly, in order to understand the phenomenon more holistically, it is important to review the extant literature on the role of information in decision-making, which is what I start with (section 3.3.1), followed by the literature on AI, data science, and decision-making (section 3.3.2). Toward the end of this section, I offer some perspectives on the distinction between data and information (section 3.3.3), which is important for this study.

3.3.1 Information and Decision-making

Information has been recognized as an integral lever in the process of organizational decision-making in IS as well as organizational theory literature. I organize the relevant literature based on the focus on the agents and their role in the process. One stream of
literature focuses on the decision-makers as the key agents and examines their role in processing (or ignoring) the information while making decisions (section 3.3.1.1), while the other stream of literature focuses on the analytics professionals who produce the information that is subsequently consumed by the business professionals in decision-making (section 3.3.1.2).

### 3.3.1.1 Decision-makers as the Processors of Information

**Information Processing Perspective.** The students of organizational theory have extensively studied the role of information in organizational decision-making processes for several decades. A prominent stream of literature within this domain is the Carnegie School tradition (e.g., March & Simon, 1958) which has examined the relationship between information and decision-making by relying on the information processing perspective (Gavetti et al., 2007). Built on the foundational work of Herbert Simon (Joseph & Gaba, 2020), the information processing perspective affords a vast and wide literature within organizational theory, and I only review a fragment of the literature that is relevant to this study.

Organizations are conceived as information processing and decision-making systems (March & Simon, 1958). Organizational decision-making and problem solving is conceived to have four broad stages: agenda setting, problem representation, search, and evaluation (Simon, 1947). Organizations need to structure the processing of information in terms of gathering, interpreting and synthesizing (Tushman & Nadler, 1978) to facilitate decision-making processes, which are performed by inherently boundedly rational humans (Simon, 1997). The notion of bounded rationality implies that managers bring and rely on a set of simplified mental models to each of the stages of problem solving (Gavetti & Levinthal, 2000). Effective information processing is posited to include “the collection of appropriate information, the movement of information in a timely fashion, and its transmission without distortion … [as well as] …the ability to handle needed quantities of information according to these criteria” (Tushman & Nadler, 1978), and advanced IS are believed to be aiding organizations in making effective information processing possible by reducing the information processing requirements (Galbraith, 1974; Huber, 1990).
Three observations can be made about the extant literature on the information processing perspective. First, the managers—individuals responsible for making decisions—are the key and only actors considered to be important in the perspective (Turner & Makhija, 2012), and are assumed to be cognitively bounded yet rational and hence logical. Second, the technologies that facilitate information processing are mostly the technologies of information storage, aggregation, and retrieval (Huber, 1990) that treat information as given, unlike the technologies that facilitate generating insights from data (e.g., AI-enabled analytics tools). Third, even though mentioned otherwise (Tushman & Nadler, 1978), information is often treated as indistinguishable from data. In other words, these studies adopt a “token view” of information (Boell, 2017), where information is an “undifferentiated commodity of data bits that are processed” (McKinney & Yoos, 2010, p. 331).

**Socio-political Implications in Decision-making.** The information processing perspective assumes bounded yet instrumental use of information in decision-making which is challenged by the students of socio-political processes. In this view, the information processing perspective—where “information is regarded as an input to decision making and the decision maker is considered a passive recipient of this information” (Schultze, 2000, p. 3)—is considered problematic, as information is often decoupled from the decision-making in organizations. There are several conspicuous features that hinder instrumental use of information (Feldman & March, 1981). Treating organizations as political coalitions, scholars in this stream of literature adopt a socio-political perspective that goes beyond the individual decision-makers’ cognitive limitations and demonstrates that the conflicts of interest between self-interested individuals or groups inevitably form the background of organizational decision making (March, 1962; March & Olsen, 1984). Instead of the available and relevant information, these studies show that choices are often being made based on the bargaining and preferences of the most powerful actors (Pettigrew, 1973).

Even though these socio-political accounts of decision-making decouple the functions of the gathering and use of information, they still treat information as given, or at least do not explicitly recognize the role of actors—other than the decision-making
managers—who facilitate the production of information. Overall, a large body of extant literature on organizational decision-making has focused on how the managers process (or ignore) information in ways characterized as boundedly rational, socially situated, or politically motivated. Such a conceptualization of information is limited as, for “[a]ny organization that dynamically deals with a changing environment ought not only to process information efficiently but also create information and knowledge” (Nonaka, 1994). Acknowledging the implications of information production helps in recognizing that the information undergoes a transformative process through which the knowledge workers (e.g., analysts) integrate their idiosyncratic knowledge and experience with the data and information within the organization before it is processed by the decision-makers (Stehr, 2015). A limited scholarship has focused on this aspect of decision-making processes, which I discuss next.

3.3.1.2 Analytics Professionals as Producers of Information

A limited scholarship has focused on the professionals who produce information to be consumed subsequently by decision-makers, with political science scholars focusing on bureaucratic analysts (Feldman, 1989), organizational scholars focusing on internal analysts (Langley, 1989), and IS scholars focusing on competitive intelligence analysts (Schultze, 2000). Information production depicts an image of knowledge work where information is not taken for granted but considered a transformative activity (Stehr, 2015) enacted by professionals. In addition to functioning as knowledge brokers (Pawlowski & Robey, 2004), these professionals also function as knowledge and information producers.

Focused on the purpose of formal analysis in three different organizations, Langley (1989) emphasizes the social interactive aspects of the process and demonstrates different ways in which incremental formal analysis occurs. Highlighting the importance of “staff people” (analysts), Langley suggests that “the value of staff analysts to managers lies not only in their expertise but also in the fact that this expertise is independent of other sources of information” (1989, p. 624). She highlights six interaction patterns of use of formal analysis in practice, most of which were either initiated by the middle or senior line managers and rarely initiated by the staff analysts. In the cases where the analysts actually took the initiative, none of their projects made it through in terms of
implementation of the analysis in decision-making. Since the focus of the study was at the meso-level of interactions, it provides limited understanding about the work practices of the staff analysts.

Grounded in the context of policy making, Feldman (1989) presents a succinct account of ‘bureaucratic analysts’—experts who use well-defined methods to produce analyses of policy problems (p. 117)—information production practices and thereby provides a more nuanced understanding of work practices of the analysts. Based on her dissertation, Feldman (1989) highlights a key paradox of information production where the bureaucratic analysts, though wanting to produce clear and straightforward analyses, eventually end up producing information that is much less decisive due to the political nature of their work practices. She highlights how the positions and analyses get watered down while obtaining consensus on the reports the analysts produced and, as a consequence, such information is not utilized in decision-making as it is not generally useful for the same. Feldman’s work included multiple government departments and organizations interconnected with each other in a complex bureaucratic structure. Yet, when it comes to intra-organizational settings the dynamics of information production for the analysts are likely to be more focused and the challenges for the analysts are likely to be slightly different. For instance, unlike how “most papers written by bureaucratic analysts [tend not to be] driven by a specific decision process” (Feldman, 1989), one would expect that, in the case of intra-organizational settings, this might be the case; the analysis might be purposeful and could be carried out with a specific decision objective, which would call for further investigation.

Schultze, along with her colleagues (e.g., Schultze & Boland, 2000), provides a further peak into the intra-organizational dynamics involved in the process of information production by competitive intelligence analysts, presenting a point of departure in IS literature from “use of information” to “production of information” (Schultze 2000, p. 3). Of the three types of knowledge workers she studied, computer system administrators, competitive intelligence (CI) analysts, and librarians, her account of CI analysts as internal consultants is of particular relevance to this study. As “archetypal gatekeepers,” the CI analysts played (or, at least intended to play) a key role in influencing the
decision-making processes in the organization as reflected in their mission statement: “[t]o lead the process for acquiring and managing knowledge about end users, customers, competitors, market dynamics and future environments, and to have this knowledge reflected in business decisions” (Schultze 2000, p. 9, 17). While producing information, these analysts endeavor to be perceived as impartial and objective by the business users (Schultze, 2000). At the same time, these analysts also strive to maintain their identity as value-adding knowledge workers which creates a competing pressure on their work practices. Sometimes their situated practices, like gatekeeping, could be at odds with the espoused practices imbibed in facilitating technology, like democratization of information (Schultze & Boland, 2000). Based on the learnings from this study of work practices of CI analysts, it would be interesting to see how data science professionals produce information in organizational settings, while playing with much larger data sets, employing the AI-enabled analytics tools, and endeavoring to fulfill the renewed promise of rationality in decision-making.

In sum, complementing the information processing and socio-political accounts of domain experts and business managers as decision-makers, this stream of literature has focused on information production as a necessary yet overlooked aspect of decision-making. I build further on this perspective while describing data science and analytics in practice literature in the last subsection (3.3.2.3) of the next section (3.3.2).

3.3.2 AI, Data Science, and Decision-making

3.3.2.1 AI-enabled Analytics Tools as the Technologies of Rationality

Over the last decade, AI-enabled analytics tools have increasingly become popular, signifying the latest iteration of technologies of rationality (March, 2006). Practitioners and the academics writing for practitioner audiences have positioned these tools against the intuitive decision-making processes of managers. Arguing against intuitive decision-making of business managers, experts have posited use of analytics in terms of “the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions” (Davenport et al., 2010). In fact, scholars have argued that with the power of facilitating descriptive and
predictive decision-making, “using big data enables managers to decide on the basis of evidence rather than intuition” (McAfee & Brynjolfsson, 2012, p. 5). Following the lead of the practitioner-oriented literature, the academic IS literature has embraced the positioning of AI-enabled analytics tools as technologies of rationality and endeavored to validate the promising proposition. Scholars have introduced novel data sources, novel ML algorithms, as well as advanced the existing algorithms to increase the predictive power of the models across industries. For instance, in the online search space, scholars have proposed methodologies for selecting relevant data associated with a specific phenomenon of interest to improve prediction (Brynjolfsson et al., 2016). In the healthcare sector, scholars have developed a novel Bayesian learning approach to predict patients’ risk of adverse health events that is expected to help healthcare professionals in making better decisions (Lin et al., 2017).

Since the literature is still emerging, the adoption and use of these tools in organizational settings is not fully examined (von Krogh, 2018). Focusing on the tools and technologies at a “discrete level,” many of the studies in extant literature attempt to explain “how managers can make better decisions once they have better data and analytic tools … [A]n implicit assumption … has been that” organizations “can capture value while continuing to function as before” (Sharma et al. 2014, p. 434). These concerns have given birth to the emergent stream of literature, which I refer to as AI in practice.

3.3.2.2 AI in Practice

AI in practice is a nascent stream of literature that has emerged recently in response to the critique of the discrete studies claiming the rational implications of AI-enabled analytics tools in decision-making. Focusing on business professionals and domain experts as information processors, scholars have largely emphasized the socio-political processes of decision-making and highlighted some unintended consequences of implementation of AI-enabled analytics tools. For instance, in a study of radiologists in a major US hospital, Lebovitz (2019) demonstrates how AI-enabled analytics tools make routine tasks more non-routine by inducing diagnostic ambiguity and doubt in producing accurate and time-sensitive medical diagnoses. In another study of implementation of a predictive tool (IBM Interact) in the call center of a large cable operator, Bader and Kaiser (2019)
demonstrate how the imbalance between the algorithmic predictions and the human agents’ decisions lead to unintended outcomes in terms of deferred decisions, workarounds, and manipulations. Similarly, in a study of strategic failure of Ferrari in the 2010 Formula 1 World Championship, Aversa et al. (2018) demonstrate how decision-support algorithms might constrain the decision-making ability of senior managers due to the affordances, distributed cognition, and performativity.

In essence, the AI in practice literature has started uncovering the organizing implications for the latest iteration of technologies of rationality and thereby started addressing the calls to study such technologies in practice (e.g., Faraj et al., 2018; Jarzabkowski & Kaplan, 2015; von Krogh, 2018). Yet, these studies have overlooked the other side of the dynamic as to how those AI-enabled analytics models are produced in the first place, which is the focus of the next subsection.

### 3.3.2.3 Data Science and Analytics in Practice

A related, but distinct stream of literature has focused on the other side of the dynamic by investigating the phenomenon of data science and analytics in practice (e.g., Carter & Sholler, 2016). In a study of the sales function of a telecommunications company, Pachidi et al. (2020) document a radical change in the sales *regime of knowing* “from one focused on a deep understanding of customers via personal contacts and strong relationships to one based on model predictions from the processing of large population-wide and historical data sets.” Such a change resulted from symbolic actions of the data scientists and the sales personnel following the introduction of a customer lifecycle management model, based on predictive modeling and optimization algorithms (Pachidi et al., 2020, p. 19). The study’s key focus was on the coordination (or lack thereof) between data science and sales professionals and the consequent implications on the sales regime of knowing following the implementation of customer lifecycle management model, with a little less focus on how data science professionals developed the model. This study resonates with the findings from Shollo and Galliers (2016) who demonstrate the performative implications of adoption of AI-enabled analytics tools to organizational knowing.
In a study grounded in inter-organizational settings, Glaser (2014) demonstrates how analytics professionals working in a professional organization inscribe their expertise into the strategy tools by the processes of prototyping, pinging, and contextualizing. Since, in this inter-organizational setting, there was a spatio-temporal separation between the production and use of analytics tools, it remains to be seen how such processes unfold when the external consultants become internal consultants.

In a field-level study of data science and analytics, Steele (2016) interacts with data scientists and analysts from various industries at conferences and demonstrates “analysts’ ideal” reflections on the design and legitimation strategies for establishing their identity and producing knowledge to be consumed by others. Since this study was at the field level, it remains to be understood as to how these strategies manifest in the work practices of the data scientists when they perform rationality and produce models and insights to be consumed by business professionals and domain experts.

Extending this line of work, this study endeavors to set forth some initial foundations of this nascent research tradition by answering the question: *How do data science professionals enact their informing practices while aiming to facilitate rational decision-making in incumbent organizations?*

### 3.3.3 Data versus Information

Before proceeding further, a distinction between data and information warrants some discussion. Building on Kettinger and Li (2010), I define data as *the measures or description of objects (and subjects) or events, usually referred to as a set of interrelated traces that measure the attributes of the objects (and subjects) or events in the real world*, which can be purposefully or un-purposefully (Constantiou & Kallinikos, 2015) collected by organizations. Although, I recognize “raw data” as an oxymoronic phrase (Gitelman, 2013), for analytical purposes this definition of data assumes the token view (Boell, 2017) and treats every token that enters the organizations and first stored in the servers as raw data. This is in line with the observer-relative approach (Demetis & Lee, 2019), where I treat the organization under study, as an observer as a whole. This
conceptualization of (raw) data is in line with the perception about data among my study participants.

Defining information is less straightforward due to the multiplicity of views prevalent in literature (see McKinney & Yoo, 2010 for a review). Even the informants whom I observed and interviewed had multiple views about what constitutes information and insights. Hence, instead of narrowly defining information, I offer a broad description of what constitutes information from the perspective of informants in my study. First, information can be produced by refining data in various ways which may or may not include advanced analytics techniques. Second, information is not independent of its producer. Third, information could be considered a model of something to someone (Floridi, 2005; Zoglauer, 1996), and hence can be treated as a form of representation of the world from the perspective of the producer. Accordingly, each representation may differ in significant ways from individual to individual, based on the subjective character of experience (Boland, 1987) and interpretation (Berger & Luckmann, 1966). Fourth, information could be described based on its consequence, in that, it is something that makes a difference (McKinney & Yoos, 2019). For instance, “a firm perceives declining sales (a difference), and the perceived declining sales make a difference to the firm, then there is information” (McKinney & Yoos, 2010, p. 337). In my empirical settings, I have observed data scientists leaning toward either the representation or difference view of information and rationality, which in turn had an influence on how they enacted informing practices.

Throughout the essay, I use information and insights interchangeably. While the term information has a more theoretical value, the term insight is very common among practitioners. It can be considered a subset of information produced after performing some mathematical or computational analytics on data.

### 3.4 Research Design and Methodology

Using an inductive approach, I analyze on-site observations, real-time as well as retrospective interviews, and archival records to understand the work practices of data science professionals. The study is grounded in the empirical setting of three large Indian
banks having incorporated their separate data science units in their quest to lean more toward data-driven rational decision-making. I start by describing the research sites following the data collection and analysis.

### 3.4.1 Research Sites: Data Science Units at Three Large Indian Banks

Data science units at FinBank, DigiBank, and InvestBank (all the references to organizations and individuals are pseudonymized to protect the confidentiality), three large Indian banks, comprise the research sites. Geographically, the sites are located at three metro cities of India including Mumbai, Chennai, and New Delhi. The data science units in these three banks had been incorporated over the last three to ten years (at the time of fieldwork). These units were identified as centers of excellence within functional areas including marketing, finance and risk management, and consumer banking. The units would typically have a leader to overlook the overall functioning of the unit, and would report to the Chief Marketing Officer, Functional Head of Consumer Banking, or Chief Risk Officer of their particular bank.

Even though they were closely associated with the Information Technology (IT) departments, the data science units were not located within the IT function in any of my research sites. The IT function still controlled the technology infrastructure, including the data warehouses as well as big data applications such as Hadoop, Tableau, and Power BI. Yet, the data science units were entrusted to use these technologies and develop their own algorithms to conduct analytics and generate insights from the data that could be subsequently consumed by business professionals. Business professionals is an umbrella term I use to represent the team members and managers in various departments and functions that are entrusted in making business decisions by utilizing the insights generated by the data science professionals.

Typically, banks organize their structure into product-based teams (e.g., liability and asset products), function-based teams (e.g., marketing, finance, audit, and operations), consumer segment-based teams (e.g., retail and corporate banking), as well as channel-based teams (e.g., branch and digital banking). At all the three research sites, the data science units were established to cater to several departments and functions, and
at the time of incorporation of these units, these banks had recruited a team of data science professionals in a combination of fresh university graduates as well as lateral hires from other organizations including banks, consulting firms, and technology firms, in line with the global trend (Davenport et al., 2020).

The three banks were among the top ten banks in India (based on the market cap). Table 3.1 provides background information of the three research sites. During the early phase of the study, I reached out to several large Indian banks using my professional connections, in particular the banks which were recognized for their adoption of advanced analytics techniques in business decisions, and eventually selected these three banks which agreed to provide access. The rationale for choosing more than one bank was two-fold. First, from my early interactions with the practitioners, I realized that there was a very high turnover among the data science talent and hence it could have been a challenge to find enough participants with sufficient tenure\textsuperscript{13} in a single organization. Second, in addition to the turnover, the size of the data science units was another aspect under consideration. In most of the banks, since these units were relatively new, the number of employees were still limited, which imposed another constraint on my ability to recruit enough participants to deeply examine the phenomenon. Accordingly, selecting three sites provided sufficient opportunity to recruit the participants from a large pool. The sampling criteria within the sites is discussed in the data collection section.

These data science units at the Indian banks provided fertile ground for identifying the processes, mechanisms, and conditions that shape informing practices of data science professionals for several reasons. First, large incumbent banks are well-known for their use of advanced technologies and information in organizing. Banks have been the front runners in adopting these tools in terms of all the waves of analytics evolution (Chen et

\textsuperscript{13}I considered six months as a cut-off to recognize data science professionals as new recruits as opposed to experienced team members. Six months was the typical probation period for the new recruits, and there was a belief among my informants that professionals who stay for more than six months are likely to spend at least a couple of years in the bank. In addition, during the first six months, data science professionals would typically undergo various trainings (including on-the-job training) and were less likely to be assigned a full-time portfolio.
al., 2012). Second, all the three banks had incorporated their distinct data science units and had not just relabeled their existing management information systems (MIS) departments or business intelligence units (BIU). This distinction in the form of incorporation of separate units, provided a unique opportunity to examine their idiosyncratic work processes. Third, at all the three banks in my sample, the data science professionals, individually as well as collectively, had been recognized in the industry (and won awards from independent agencies) for the data science solutions they had implemented in their respective banks. Forth, India is only second after China in terms of the average FinTech users, which puts the banks under pressure to use advanced analytics to remain competitive. Accordingly, the data science professionals are expected to cater to data-driven decision-making by working in conjunction with other more traditional units (e.g., liability product teams, retail assets teams, digital banking teams, IT teams) of the banks.

### 3.4.2 Data Collection and Analysis

Data were collected and analyzed following a qualitative case study approach (Miles & Huberman, 1994; Yin, 2014). The initial conceptualization and informal interaction with the digital transformation leaders in the banking industry started in spring 2018, with the formal data collection spanning the period of January 2019 to June 2020 (I physically entered the field in April 2019 and exited in December 2019—with first month spent in familiarizing with the context; the interactions before and after happened virtually). The data sources included on-site observations (at FinBank and DigiBank), semi-structured/retrospective interviews, informal/real-time interviews, and archival records. The observations included shadowing the informants and attending meetings at FinBank and DigiBank. The data from these two sites were pooled to generate the key insights, while the data from InvestBank were collected toward the end of the study to validate the key findings from the first two sites until reaching theoretical saturation. Table 3.2 provides a summary of data collection.

At all the sites, the leaders of the data science units or the senior functional managers granted the access to conduct the research. The heads of data science units at the sites introduced me to their teams either during a common meeting or by circulating
an introductory email. The selection of study participants was opportunistic as well as theoretical. It was opportunistic because I was reliant on the volunteers who would agree to be observed and/or interviewed at the three sites after the initial introduction. It was also theoretical, as my decision about subsequent observations and interviews were based on the analysis of initial observations and interviews which led to emerging puzzles, refinement of the focus of observations and interview questions, and a quest for finding deeper dimensions of the theoretical constructs. My unit of analysis was informing practices enacted by the data science professionals.

3.4.2.1 Observations and Real-time Interviews

Observations are one of the key sources of my data. At two of the sites, FinBank and DigiBank, I spent between five and six days a week observing the data science professionals’ day-to-day work (Van Maanen, 1988). The study participants were typically a subgroup of professionals whom I shadowed within the data science units at each bank while these professionals were collaborating on one or more projects during the observation period. I observed them enacting their day-to-day work processes individually, interacting with their colleagues on a particular topic or troubleshooting informally, and interacting with colleagues, seniors, and business professionals in the form of formal meetings. In all of my observations, I was more of an observer than a participant (as I did not contribute to any of the team activities formally), although, I was assigned a desk among the team members and had ample opportunities to interact with them.

Due to the nature of work involving experimenting with advanced analytics tools, there was inherent opacity (Beane, 2019a) in the work practices of the data science professionals. For instance, they spent hours sitting in front of their computer screens, sometimes without uttering a word. From a distance, this work seemed monotonous and trivial to me as an observer, as I only heard the sounds of the keystrokes and corresponding changes on the screens. Yet, during these long hours the data scientists would have been grappling with various activities including writing codes, pre-processing data, fitting models, interpreting the outcomes, and then re-writing codes. In
order to make sense of this style of work, I followed a few strategies that involved informal interactions and interviews (Spradley, 1979) with the participants.

Typically, I would first look for the occasions when the participant would seem less engaged with the work, to initiate a conversation. For instance, at my sites many of the participants would typically work for 20 – 25 minutes at a stretch and then take a pause in the form of peeking into their mobile phones, switching the screens to check emails, picking up a phone to talk to a colleague, and so on. I would make use of such pauses to engage. I would ask questions regarding my observation of the preceding time block in terms of why and how they did, what they did. Second, sometimes the pauses also took the form of informal interactions among colleagues. Most of the participants used to take breaks after having spent a couple of hours on their computer screens. They would walk up to their colleagues, discuss some ideas, interpretations or concerns they faced, and engage in a discussion with them. For me, such interactions were great opportunities to learn about what was going on, without asking them specific questions. These informal discussions among the professionals were very common and formed a considerable part of my observational data. Third, at both sites, I followed office hours similar to the participants and hence they eventually started treating me as an insider. I also joined them during tea\(^\text{14}\) and lunch breaks on all the days during my presence at the sites. These occasions again provided additional data points to understand their work with more context. Finally, at DigiBank, I shared a train ride with an informant in commuting to and from the office for most of the days (approximately a two-hour ride).

These informal interactions with data science professionals afforded a chance to probe deeper into their formal work and they were able to share insights freely during these interactions. During my observations, I paid close attention to the work practices around refining data, presenting the summary data to business professionals, variables selection for modeling, algorithm selection, results interpretation, insights sharing,

\(^{14}\)Tea (as opposed to coffee) breaks are very common in India. It is a common practice for the team members to walk out of their offices and take short (5-10 minutes) walks to the roadside tea stalls, to have tea, smoke or have some snacks.
stopping the analysis to move on to the next project, as well as problem solving practices. On many occasions, my questioning lasted 15 – 20 minutes, but on some occasions, the nature of the topic would require a longer discussion. In such cases, I would wait until the participant was relatively free to discuss the topic at length later in the evening the same day or the day after. I was able to record and transcribe these real-time interviews on most of these occasions. In the case of the shorter probs, I would take extensive notes to be expanded later, mostly within 48 hours.

3.4.2.2 Semi-structured Interviews

In addition to the observations and real-time interviews, I conducted formal semi-structured interviews at all the sites. I interviewed almost all the team members of the data science units at FinBank and DigiBank. The order of interviews was decided based on the availability of the informants as well as based on the themes emerging from my ongoing observations. For instance, during the observation of a modeler at FinBank, I realized that some of the choices he made in his modeling were dependent on the work of the data engineer in the team. Hence, I reached out to the data engineer to develop a holistic perspective on the information workflow. From that interview I further realized the interdependence of the data engineer and the reporting analyst.

These interviews were semi-structured and hence retrospective in nature. There were broadly two sets of interview protocols prepared (see Appendix B1), one for the data science professionals and the other for the business professionals, although the questions were asked in order of the direction of ongoing discussion, which often did not match with the order in my interview protocol. The initial interviews were open in nature. At the end of each interview during the initial period, I asked the informants to talk freely about any other aspect of their work practices that was not covered in the interview, but that they would consider to be an important aspect of their work. The informants shared several insightful details, some of which formed part of formal questions in subsequent interviews and helped in theoretically sampling further interviews. As the study progressed, the interviews became more pointed to specific themes.
Toward the end of the study, a few interviews were conducted at the third site, InvestBank. A sample of the team members from the data science unit at InvestBank were interviewed mainly to validate and theoretically saturate the findings from the other two sites. In other words, this site worked as a replication (Leonard-Barton, 1990) of the first two sites. The interviews at this site were more pointed than the ones at the first two sites. Overall, I conducted 67 formal interviews from which 50 were audio recorded, while extensive notes were taken for the remaining interviews. The notes were typed and expanded toward the end of the day in most cases and in a few instances within 48 hours.

The interviews with the business professionals were typically 30 – 40 minutes long. The main purpose of these interviews was to understand their perspective on the utility of information produced amid the increasing use of AI-enabled analytics tools and how they factor the information in their decision-making. My access to the business teams was limited, and mainly through the data science professionals. I identified the business professionals based on my discussions with the participants and interviewees from the data science units. Whenever a data science professional would refer to a particular business professional, I would request them for an introduction and then reach out to the business professional for an interview.

3.4.2.3 Archival Records and Information Artifacts

During the fieldwork I had an opportunity to review various archival records including organizational charts, proposals from analytics consultants, and process manuals. While interacting with my informants, I also got a chance to glance through various information artifacts including the data structures, algorithmic codes used in modeling, the model outputs, representation of insights in the form of slides, text documents or emails, and automated dashboards. Because of the information security protocols and concerns related to customer privacy at the banks, I was not allowed to make copies of any of the documents. I was able to view the artifacts on the computer monitors to take notes. These archival records and artifacts played an important role in shaping my understanding about the role of representations in information production and consumption.
3.4.2.4 Data Analysis

Data were analyzed iteratively and abductively following the tenets of grounded theory (Strauss & Corbin, 1990). The first few interviews and the early informal interactions with the practitioners helped “focus” the study before more formal analysis (Lofland et al. 2006, p. 119). At this stage I was able to draw a picture of the overall workflow of data and information, and acquaint myself with various roles within the profession of data science and various touch points of the interactions of data science professionals with the business professionals in the respective organizations. I also started understanding the nature of projects typically undertaken by data science professionals (e.g., attrition model, win-back campaigns, next-best products, underwriting models, dashboard automation, and robotic process automation). This initial phase of focusing helped me figure out where and what to look for while collecting the data. It is noteworthy that up to this point, in my data collection, I used organizational sensemaking (Weick, 1995) as a guiding lens (Suddaby, 2006). However, based on these early encounters in the field, I decided to drop the lens, at least for the time being. Specifically, I did so as I started constructing the workflow of data and information; from the servers of the banks in the form of (raw) data to the computer screens of business professionals in the form of insights, I realized the transformative nature of the processes and practices. I found the sensemaking theory to be less suitable as a lens to unpack these processes and practices that transform information several times before it gets consumed in decision-making. At this stage, I dropped the theoretical lens, and instead started focusing on the informing practices (work practices of knowledge workers, see Schultze, 2000). From this point forward, the informing practices of data science professionals became my units of analysis.

With the focus on informing practices, I developed a map of various practices enacted by the data science professionals in their day-to-day activities. In order to observe and understand the diverse practices, I sampled my informants based on the role they played in their respective organizations (e.g., data engineers, reporting analysts, data analysts, and modelers), each of which produced specific information artifacts (e.g., transformed data stored in data warehouses, insights represented through automated
dashboards, insights shared through PowerPoint slides, and so on). As I coded the practices enacted by distinct roles, I realized that for each of the practices, the data science professionals made specific choices (e.g., selecting data tables, selecting independent variables for modeling, deciding on reporting parameters, and so on) that were salient for the practice under observation. These choices became an important part of my codes and categories, which facilitated identification of themes. A major theme that emerged during this exercise was the practice of inscribing expertise into the models and insights generated by data science professionals that was constituted by the practices of funneling the data, representing the present, and predicting the future.

As I started interacting more with the business professionals, I started making connections between the work of data science and business professionals. I identified new, practices that the data science professionals enacted while sharing their insights with the business professionals that were over and above the work practices of inscribing expertise mentioned above. I also uncovered that oftentimes such practices of sharing insights with the business professionals were enacted by business analysts, a specific role in data science function. I realized that the practices of interacting with business professionals were also enacted by making various idiosyncratic choices (e.g., identifying the right business problems to work on, deciding the sales pitch while sharing insights, and so on). Again, these choices facilitated identification of themes. I discovered the theme of prescribing insights during this stage, a practice that was enacted by selecting the business problems/analytical insights, translating the problems into statistical narrative, and selling insights/insights-problems pairs to business professionals.

Having discovered the salient choices (“what”) for each of the major work practices, I then I recoded the data, to understand how those choices are made in practice. For instance, in the earlier stages of analysis, I discovered that data science professional needs to decide which data are important and relevant to bring into the data warehouses while enacting the practice of funneling the data. In this stage, I paid attention to how data science professionals decided on the importance and relevance of the data. I followed the same logic for all the informing practices identified during the earlier stages. At this stage I identified some challenges the data science professionals face while
making those choices, as they strived to facilitate rational decision-making. The eventual analysis was then based on “making comparisons” (Corbin & Strauss, 2008, p. 69) between the two informing practices identified earlier, inscribing expertise and prescribing insights.

I proceeded with making comparisons by engaging with the relevant literature, in particular the recent studies on data science and analytics in practice (Glaser, 2014; Pachidi et al., 2020; Steele, 2016), the seminal studies on information production (Feldman, 1989; Langley, 1989; Schultze, 2000), the literature on technologies and agents of rationality in practice (Cabantous & Gond, 2011; Jarzabkowski & Kaplan, 2015), and the literature on decision-making in Carnegie school tradition (e.g., March & Simon, 1958). This exercise of engaging with theoretical underpinnings helped me positing my findings in the context of extant literature. For instance, I was able to identify distinct challenges faced by the data science professionals while solving business problems depending on the inductive or deductive nature of the problem-solving and the professionals initiating the project (business professionals vs data science professionals).

At this stage, I focused my further data collection and analysis on that direction that allowed me to observe and analyze the paradoxical tensions between the practices of inscribing expertise and prescribing insights due to various factors, and the mechanisms adopted by data science professionals in addressing some of those tensions. In the following, I elaborate my findings on the informing practices of data science professionals. The findings are organized in the emergent order of the data analysis and theorizing, and do not imply any specific temporal order of the enactment of the practices.

### 3.5 Findings

I start the section by picturizing the *problem solving and decision-making processes* at my research sites. Though not directly related to the work practices of data scientists, these processes enforce the context—through the nature (inductive versus deductive) and pathways (business professionals-initiated vs data science professionals-initiated) of problem-solving—within which the data science professionals enact their informing
practices. Next, I explain the two key informing practices that the data science professionals enact in performing rationality, which I refer to as *inscribing expertise* and *prescribing insights*. While the practice of inscribing expertise involves refining data and generating insights, the practice of prescribing insights facilitates the solution of business problems, each of which is constituted by several subpractices. Together the two practices constitute the informing practices through which data science professionals perform rationality by making various salient choices in each of the practices, within the context of problem-solving and decision-making processes in practice. Subsequently, I demonstrate how the context of problem-solving processes influences the way data science professionals make those salient choices, often leading to *paradoxical tensions* between the inscribing and prescribing practices. I finally show how data science professionals *embrace the paradoxes* and work around such tensions.

### 3.5.1 The Context of Problem Solving Processes

Almost all the study participants hinted at two characteristics of the problem-solving and decision-making processes that influences their work practices—the nature of problem-solving process, i.e., inductive versus deductive, and the pathways through which the problems travel, i.e., problems being initiated by the business professionals versus data science professionals. I refer the projects initiated by the team of business professionals as *Pathway I* projects, while the projects initiated by the team of data science professionals as *Pathway II* projects. These two characteristics constitute the context within which the data science professionals enacted their work practices. Figure 3.1 articulates these two dimensions of the problem-solving processes.

Solving problems deductively implied that there were certain issues already recognized as problems within the organization. This recognition of issues as problems and the requirement for solving such problems might be triggered within a team of business professionals (Pathway I) or within the team of data science professionals (Pathway II) as well. The process of deductive problem solving resonated with the image of problem-solving recognized in the Carnegie School tradition to an extent, involving setting an agenda (or problem domain), representing and formulating the problem, searching for alternatives, and evaluating alternatives (Simon, 1947). Yet, there were
some noteworthy distinctions that I observed at my sites. First, many of these practices in solving problems were enacted by data science professionals as well (as opposed to only business professionals), and the nature of involvement of data science professionals was dependent on the pathways (I or II) of the project. Second, in context of data science, the solutions were not merely searched (lying there waiting to be identified) but were also being developed through the practice of inscribing expertise as explained in the previous section.

On the other hand, solving problems inductively implied that the problems were not pre-defined. Rather, the problems were discovered based on the insights inductively generated from data. Again, such discovery could be done by the business professionals (Pathway I) or data science professionals (Pathway II). The processes of inductive problem solving resonated with the image of organizations functioning in surveillance mode to inductively scan the environment (Daft & Weick, 1984; Feldman & March, 1981). Such an inductive environmental scanning under Pathway I would require business professionals to access the (raw) data themselves and identify the hidden patterns which might serve as insights for inductive problem solution. However, my findings suggest that with the increasing diversity and size of the (raw) data stored in banks’ servers, and with increasing use of advanced analytics techniques to process such data, the business managers have been increasingly decoupling from the (raw) data and increasingly relying on the visualizations and curated dashboards prepared by the reporting analysts and visualization experts instead. In other words, the surveillance function is partially being handed over, or at least being mediated, by the data science professionals. For instance, a reporting analyst described:

“Few years back, business managers used to ask for raw data in Excel sheet for their own oversight, now they mostly use visualization tools or summary data shared by us.”

With this background of problem-solving processes, I explain the work practices of data science professionals in the remaining subsections of this section.
3.5.2 Inscribing Expertise

Across the three research sites, I observed several common practices that data science professionals enacted in *inscribing* their expertise—in statistics, computer science, and analytical thinking—into the data they refine, the models they build, and the insights they generate. Starting from (raw) data to generating insights, the data and information are transformed several times through a series of practices that include *funneling*, *representing*, and *predicting*. Each of the practices transform the input data (or information) and produce refined information artifacts, which sometimes constitute intermittent artifacts that serve as input to the subsequent practice, while some other times constitute the insights that are ready to be consumed by decision-makers.

Throughout my findings, I refer to the decision-makers as the business professionals who are the stakeholders responsible to make the decision—the consumers of information—while data science professionals are responsible to inscribe their expertise into analytical tools and prescribe the insights thus generated to the decision-makers to factor in their decisions—the producers of information. In line with the practitioner literature (Harris et al., 2013; Schutt & O’Neil, 2013), I find that data science is not a homogeneous profession and it hosts people from diverse backgrounds performing diverse tasks working in diverse industrial settings. Accordingly, I refer to data science professionals at the team level, as the profession is the confluence of several functions coming together to produce information.

Table 3.3 provides an overview of the informing practices of inscribing as well as prescribing. The table also lists tasks performed by the typical roles found in data science units while using various analytics technologies and making several choices along the way. It is noteworthy that this is not an exhaustive list of all the informing practices, rather a list of the most salient work practices observed in my study. As I describe next, these practices are interdependent, and each practice warrants some salient choices to be made by data science professionals.
3.5.2.1 Funneling the Data

The practice of funneling is the founding pillar of informing practices of data science professionals. This practice is typically enacted by data engineers, but occasionally performed by other team members as well. The practice starts with locating relevant and important data that are stored in various servers of the organization. For analytical purposes, I treat these data as the raw data which flow into the organization from the real world through various banking systems and channels. Having identified the relevant and important data, the professionals engage in rigorous practices of extracting, transforming, and loading (ETL; for more details, see Qu & Jiang, 2019) the refined data into the data warehouses and data marts of the respective banks.

I term this practice as funneling as it is one of the most salient choices the data science professionals make while enacting this practice. The professionals engage in funneling—filtering out the noise, so to speak, and selecting in the signal—before formally beginning the ETL activities and storing the transformed data in data warehouses or data marts. In the banks, the data flow into their servers from various systems that include transactional and profile data from core banking systems, internet banking, merchant banking, mobile banking, and behavioral traces from various interactions. Again, within each data source, there might be hundreds of indicators (can be visualized as columns in an Excel sheet) which could be potentially included in the data warehouse. However, not all the data are relevant and important in business decision-making. For most of the other informing practices of the data science team, these transformed data stored in the data warehouses and data marts form part of the truth through which they see the world, and hence played a vital role in performing rationality. Its noteworthy that performing ETL functions on the exhaustive data collected by a bank was considered practically impossible for data science professionals, as it involved integrating the data from multiple sources into a single truth.

A simple example would be data related to a particular customer who holds a savings and a checking account with the bank, investments with several mutual funds and stocks through the bank’s investment accounts, insurance products, loans, and a credit card. Data related to transactions can potentially flow from digital banking channels,
branch banking channels, merchant outlets where the customer swipes debit and credit cards, third party channels (e.g., mutual funds), and so on. Similarly, behavioral data can flow from the websites of respective organizations, merchants, third party partners, social media, and so on. Extracting, transforming, and loading all the data for all the customers, of all the types, flowing from all categories, would be a time-consuming activity which would impact the business as usual of the other units and data science professionals who are reliant on the data stored in data warehouses and data marts. There are tools available\textsuperscript{15} for data science professionals to automate part of the process, but the tools still need to be told which data to choose, from where, and how to integrate them. The time sensitivity and automation make the choice of funneling a crucial, non-trivial practice through which data science professionals add value. As a data engineer narrated during an informal interaction:

\textit{It’s a dirty job, no one wants to get their hands dirty, but everyone wants to eat the cake ... over the years, the technology has improved. In the old times we used to record the transactions on a CD drive and manually load those data into the servers. Now the data are freely flowing into the servers, not only from transactions but also from customers’ social media and click streams. The challenge is to decide what you actually want in the data warehouses, and what you want to leave out ... I add value by making the right choices. New data bring newer challenges and newer puzzles, and that’s what keeps me going.} [informal interview, FinBank]

3.5.2.2 Representing the Present

Representing information in a way that is accessible to business decision-makers is another salient informing practice enacted by data science professionals. These practices are typically enacted by reporting analysts and visualization experts, though depending on the idiosyncratic team structure, it can be performed by data engineers, and data analysts on the team as well. Reporting analysts and visualization experts normally use the transformed data stored in the data warehouses as their input and represent summarized information that is considered relevant and important for the business decision-makers.

\textsuperscript{15}See for example, https://docs.microsoft.com/en-us/azure/architecture/data-guide/relational-data/etl
The key choice in this practice involves figuring out how to represent the information in a way that is meaningful to the stakeholders. Dashboards prepared in macro-enabled Excel sheets are typical examples of the information artifacts produced by reporting analysts, while the Tableau or Power BI are typical examples of automated dashboards prepared using visualization tools. The representational choices that data science professionals make involve the parameters to be included in the dashboards, the method to employ in measuring the performance of those parameters, as well as the frequency of updating the dashboards, among others. Another important choice in this practice is to ascertain why and when to drop a parameter from, or to introduce a new parameter to, the dashboard. These choices are consequential as, based on the information represented, firms ascertain their performance against aspirations (Cyert & March, 1963) and take strategic decisions accordingly. In other words, the representing practice by data science professionals facilitates and often mediates the monitoring practice of business professionals. As narrated by the visualization expert in one of the banks:

“Most data science and analytics projects start from monitoring [by business professionals], which is facilitated by reporting done by us. Reporting is not new. … What has changed is reporting has progressed from Excel-based summaries to representations developed by tools. …, we provide insights about what is going wrong … along with potential explanations. … But it depends on what business also wants … reporting is an art of balancing what the business wants to see, and what I think is important for them to see.” [interview, DigiBank]

It is noteworthy that this practice of representing sometimes also involves funneling as well as modeling. For instance, it may involve developing measures using statistical and computational modeling techniques and representing those measures in the dashboards. In one of the banks, while building a dashboard demonstrating the performance of a savings accounts portfolio, a reporting analyst included a measure of net worth of the customers to represent the quality of acquisition. However, the parameter of net worth was modeled based on other indicators including account balance, loan instalments, salary credits, and investments. However, I term this practice as representing, as it demonstrates the most salient choices the data science professionals make in this practice.
The informing practices of funneling and representing are very time sensitive. The data science professionals tasked with these activities are usually the busiest in the team. Their work impacts the *business as usual* and hence they need to be very cognizant of the time they spend on any activity.

### 3.5.2.3 Predicting the Future

In addition to funneling the data and representing the status quo, data science professionals also enact a practice of predicting the future through their expertise in exploring, analyzing, and modeling. These practices are typically enacted by the data analysts and modelers\(^\text{16}\) in the team. While both data analysts and modelers at the three sites generated insights by analyzing the transformed data (or information artifacts) stored in the data warehouses and data marts, the key difference was in their expertise. For data analysts, the tools that generally came in handy were Structured Query Language (SQL) and SAS (a statistical software by the SAS Institute), with which they played with the data by taking different cuts, summarizing them in distinct ways, and preparing charts. At times they also ran basic statistical models. Their expertise lied in their ability to see the trends in the data and to extrapolate the trends in predicting potential scenarios. While, in the case of modelers, they also engaged with the data in a similar manner, yet their core expertise lied in their ability to build the statistical and computational models that met the standards of fidelity. The predictions in their insights were based on the outcomes of their models. For instance, an informal interaction with a modeler at FinBank revealed his perspective on modeling while describing the attrition model he was building:

*My job is to build a model that can predict the future ... so that bank can take timely action. This [attrition] model I am building, will predict which customers are likely to stop using their savings account with us, if we don’t do anything. ... I try to build models which confirm to the standards of confusion matrix. If it meets all the three standards, of accuracy, recall, and precision, I*

\(^\text{16}\)Some practitioners as well as academic scholars refer to these professionals as data scientists in generic terms, while some identify these professionals with very specialized roles such as AI modeler or ML expert. Yet, a common skill that these professionals have is their ability to build statistical and/or computational models to predict some outcomes based on relationships among the predictor variables.
would be happy. I would be happier if I can beat my own past performance. It all depends on the data I have, the feature engineering I do to create variables, the algorithm I use, and the way I set the values of hyperparameter. Modeling needs a lot of patience, understanding of business problem, and ability to apply my statistical and computing skills to solve given problem. [informal interview, FinBank]

While continuously striving to predict the future, data analysts and modelers have to make several important choices. For example, while building a predictive model, a data science professional has several algorithms and modeling techniques to choose from which may or may not involve ML. The professionals also needs to make choices about which variables to choose as independent variables. Even though one can throw tens of variables into the model, the person still needs to choose those tens of variables from the list of hundreds of indicators. The variables also need to be constructed in line with the nature of the outcome being predicted. One of the common activities of all the modelers is spending time on feature engineering to extract features from transformed data that can be used to improve the performance of algorithms. An equally time-consuming activity is hyperparameters tuning. As is evident, the data analysts and modelers would also engage in various funneling and representing practices, but I refer to this practice as predicting as that is the goal they are chasing.

Some observations warrant further discussion before concluding the section. First, I have organized this section around the work practices and not around the roles, as the roles are fungible. For instance, a modeler sometimes extracts raw data from the servers directly (as opposed to using the transformed data stored in the data warehouse) to build a model, and thereby doing the job of a data engineer. In that case, a single data science professional engages in more than one of the practices identified above. So, exact roles of the professionals who would enact a particular practice would be idiosyncratic to the organizational structure and culture, yet the practices identified here are likely to be common irrespective of such idiosyncrasies. Second, the informing practices of the data science professionals are intertwined and interdependent. Each informing practice invariably involves elements of the other practices (e.g., predictive modeling involves funneling and representing) and are also dependent on what has been done in the other practices (e.g., predictive modeling is conditional on the transformed data stored in the
data warehouses during the funneling practices). These interdependences are similar to the sequential task interdependence identified in the literature (e.g., Thompson, 2003).

3.5.3 Prescribing Insights

The informing practices of inscribing expertise into models and insights only provide a partial account of what data science professionals do. The insights generated also need to be prescribed to business professionals in order to influence decision-making. The work practice of prescribing insights involves more direct interaction with the business professionals and signifies a point where the data and insights meet the business problems, and take shape of the business solution. Accordingly, I explain three key subpractices that constitute prescribing insights in correspondence with the problem-solving processes that include, selecting the business problems/insights, translating the problems in statistical narratives, and selling the insights/insights-problem pairs as solutions to the business professionals.

3.5.3.1 Solving Known Business Problems Deductively

Selecting the business problems is one of the most salient practices, often constituting the first instance of interaction between the data science and business professionals in deductive problem solving processes under Pathway I (most of the deductive data science projects at my sites followed Pathway I—initiated by business professionals). Business managers and team members played a key role in formulating the problems under a specific problem domain. Once the problems were formulated some of them were shared with the data science teams in search for solutions, typically through the business analysts. Business analysts can be considered the data science professionals who often span the jurisdictional boundaries and work closely with the business professionals. When presented with a request from the business professionals, the business analysts enacted the practice of selecting the business problems based on their expertise. Naturally, the business analysts selected only few of the problems the business professionals proposed to solve with the help of data science professionals. While enacting the selecting practices they engaged in actively judging which projects need to and can be solved by data science teams in such a way that they can bring rationality to
decision-making. For instance, a business analyst explained his experience with business professionals:

“You have to be very careful in identifying the right problems. The business professionals often bring you the problems which are either not worthy of data science [e.g., data extraction requests] or are not part of their top priority. If you accept such problems, you will either get sucked into non-value adding tasks or the projects will go on perpetually as those are not in the priority list of senior management.” [interview, FinBank]

It is noteworthy that the practice of selecting is only salient in the case of deductive projects, which start with a stipulated problem. In the case of inductive projects, the data science professionals enact a practice of selecting the insights instead, which is described in the next subsection.

Having selected the business problems, the business analysts then enact the practice of translating the selected business problems into statistical narratives that the remaining team members in the data science unit could understand and act upon. In enacting this practice, the business analysts often needed to carefully craft a statistical narrative and clarify the problem definitions in statistical terms. For instance, in the case of an underwriting automation project, there were several iterations between the data science and business teams in agreeing on what is a measure of creditworthiness should mean.

Data science and business professionals had a heated debate about how to ascertain if a customer is creditworthy to be granted a loan from the bank. The policy [business team responsible for underwriting process] understood creditworthiness basis the customer’s credit rating from CIBIL [an independent credit rating agency], but not all the customers had CIBIL scores and if data science professionals included the score in the model as a predictor variable, it would be correlated with many other variables... overpowering other important indicators due to high information value. A lot of discussion went in to defining creditworthiness, even before our team started modeling. [fieldnotes, DigiBank]

Again, the practice of translating is only salient in the case of Pathway I projects, where the problems need to cross the jurisdictional boundaries between the business and data science teams. In the case of Pathway I projects, such a translation is not required, as the problems are often defined in the statistical language to start with.
Subsequently, the rest of the data science professionals in the team enacted the practices of inscribing their expertise by funneling, representing, and/or predicting practices. The respective data science professional who produced insights, along with the business analyst who translated the business problem, then together would pair the insights with the stated problem with an objective to reduce the uncertainty and eventually engage in selling the rational solution to the business professionals. The business professionals (in most cases) accepted the solution, and thereby closed the loop of the deductive projects under Pathway I. A team leader while sharing her experience:

“After doing everything, we still need to convince the business professionals that the solution we prepared is the best suited for their needs. Though, most of the heavy lifting for these projects [Pathway I projects initiated by the business teams] is generally done upfront during the early negotiations. Once we agree on the problem definition, etc. the project generally sails through”. [interview, FinBank]

Some observations about the deductive problem solving practices. First, one of the most salient choices in this practice of prescribing insights by solving deductive problems was type of problems that get selected to work on, which was jointly decided by the business and data science professionals. However, the balance of the control over problem formulation was dictated by whether the project was initiated by business (Pathway I) or data science (Pathway II) teams. Since, most of the deductive projects at my sites were initiated by business professionals (Pathway I), they controlled which problems to bring to the data science teams, while the data science teams controlled which ones to select from the list brought to them. Yet, their ability to reject the projects was limited. Second, in addition to the choices the problems, oftentimes the business professionals also envisioned what the potential solution might look like. In other words, the deductive processes often entailed close-ended problems. One of the modelers explained,

“You know, the product [business team] people, they have their own preferences about how to build the models. They would typically have some ideas about one or two variables that should predict the outcome. Since they brought the problem to us, I can’t deny such ideas upfront. I generally include their recommendations in the models. ” [interview, DigiBank]
### 3.5.3.2 Solving Novel Business Problems Inductively

Most of the inductive data science projects at my sites followed *Pathway II*—initiated by data science professionals. Although, compared to the deductive projects, the inductive ones were much fewer. In fact, most of my informants suggested that over the span of their tenure, from the total projects they had handled, only 20-30% were inductive in nature. As described previously, in the case of inductive problem solving, the practice of selecting the business problems is replaced by the practice of selecting the insights. A key starting point for such projects is the practice of conducting exploratory data analysis the data science professionals, without an a-priori problem in mind (part of the *predicting* practices explained in the previous section). Correspondingly, a salient choice they needed to make included the decision about where to look for the data in anticipation of finding something interesting and novel. Naturally, they engaged and enacted all the practices of funneling, representing, and predicting, as they inscribed their expertise in the models and insights, but this time, without a specific end goal. For instance, a data analyst narrated her experience in working on a cross-sell project for salary accounts:

> *I love playing with the data. While working on my routine projects, I often come across some unique trends, which I explore further. You can generate 100s of insights while exploring the data, but you never know which one to pursue further and to what extent. I often keep going. If you look enough, you will find something interesting. But, which of those interesting insights are important and relevant for business, is a choice you have to make.* [informal interview, FinBank]

Enacting predicting practices through exploring was a time consuming, yet rewarding activity. The data science professionals kept going until they thought they were on to something that could potentially change the extant business strategy. Such an exploratory analysis often resulted in several insights, which could potentially work as solutions to various business problems. An important choice the data science professionals had to make here was to select the insights that should be taken forward to the business professionals. To make this choice, they had to imagine potential problems they could solve with those insights, which was often done with the help of business analysts.
Once they felt they were on to something, they, along with the business analysts in the team, would engage in selling the rational insights-problem pairs to the business professionals. Business teams, in turn, accepted/rejected the proposal, fully or partially, and possibly shared some feedback with the data science teams to make further changes.

Selling is one of the most important practices in the inductive projects. As most of the inductive projects get rejected at this stage for various reasons. For instance, a business analyst narrated while explaining about a checking account portfolio penetration project:

*Data science professionals could have brilliant ideas and state of the art models, but if they are not able to convince the business, they will easily reject the solutions. Data science professionals often need to walk an extra mile and demonstrate [to business professionals] as how to use the solution in their decisions and not just share the solution. On the other hand, sometimes data science professionals might be able to sell insights based on very simplistic models as well. The key is to be able to position the insights into business priorities and find the sweet spot, something very new, which they [business professionals] are willing to try.* [fieldnotes, FinBank]

Some observations warrant further discussion before concluding the section. First, like the previous section, I have organized this section also around the work practices and not around the roles. Even though I have narrated the practices by demonstrating the role played by business analysts, the same practices could also be enacted by the team leaders or other senior data science professionals on the team as well (e.g., modelers, data analysts). Second, in the practices of prescribing insights, the business professionals also enact problem-solving practices, however, since the focus of my study was on the work practices of the data science professionals, I did not collect observational data about the work practices of business professionals. Also, there were many projects for which the business professionals solved the problems internally, without involving the data science professionals. Such projects were beyond the scope of my inquiry. Third, the informing practices of inscribing expertise and prescribing insights are deeply intertwined and practically inseparable. In practice it is not feasible to draw a clear line where one set of practices stops, and where the other starts. Yet, I chose to present them separately for analytical purposes with an aim to explain the phenomenon more clearly.
In the next section, I elaborate on how the choices are actually made by bringing the two informing practices together, and demonstrate how the context in which the choices are made leads to paradoxical tensions.

### 3.5.4 Data Science and the Paradoxes of Rationality

The data science professionals at my sites identified themselves as the *custodians of rationality*, having the responsibility and ownership of facilitating rational decision-making, a conceptualization that resonates with the image of analysts as the “prescriptors of rationality” (Cabantaus & Gond, 2011) who work as “internal consultants” (Schultze, 2000) for the organizations. For instance, the head of the data science unit at one of the banks mentioned:

> “The bank has set up this department to make good use of analytics in making rational decisions. It is my responsibility to make that happen. The business managers have been there for years, and they will keep making their decisions as usual, unless I actively intervene and make sure to provide them with the right information to make decisions based on the evidence and data.” [Interview, FinBank]

They perform their role as the custodians of rationality by enacting the informing practices of inscribing expertise and prescribing insights by making several salient choices. My findings suggest that the context within which these choices are made at times brought paradoxical tensions for the data science professionals. In this section, I explain some of the paradoxical tensions resulting from factors including the conception of meaning of rationality among data science professionals and their coordinating practices within and across the boundaries of expertise.

#### 3.5.4.1 The Meaning of Rational Decision-making

Even though they self-identified as custodians of rationality, the data science professionals did not agree on the meaning of rationality unanimously. I found two broad perspectives on the meaning of rationality in decision-making at my sites—one conceived rational decision-making as acting on the insights that *signify the best representation of the world*, and the other conceived rational decision-making as acting on the insights that *make a difference to the world*.
The data science professionals who aspired to build the best representation of the real world with the insights they generate tended to work closely with the data. They spent a lot of time in an attempt to “let the data speak.” They were very careful and particular about how to proceed with the modeling. They would take hours in tuning the hyperparameter until their whole body agreed with the outcome. They would spend time in feature engineering and develop hundreds of variables to feed into the models and then choose the best predictors with the highest information value. Their idea of performing rationality in the organization was through building the best representation of the real world and using that representation in making rational decisions. These professionals did not like business managers intervening in their work and hence drew clear boundaries. They only involved the business users when they thought that they had a compelling case to be made with a perfectly crafted model of the world. They did recognize that there might still be biases in the models they created and insights they produced, yet they endeavored to make sure that the biases were their own. For instance, a data analyst described her perspective:

“Data science is a complex process that involves collaboration among multiple team members who have their own choices and preference. Because of so many people involved, the presence of biases in our models and insights is inevitable. However, my endeavor is always to ensure that if my insights are biased, those biases should mostly be mine and not of others.” [interview, FinBank]

They generally struggled in deciding when to stop and tended to engage in perpetual modeling, deriving incremental satisfaction from incremental improvements in the model. Success to these professionals lied in their ability to beat their own records from the past and in scoring higher in all the parameters of the confusion matrix. In other words, they paid much more attention to inscribing expertise into the models and insights, but found themselves in a weak spot when it came to prescribing the insights to the business professionals. A modeler explained during a break when I asked him about the success parameters:

Playing with data and improving my models are my most favorite tasks. My job is to build the perfect models. I have my own standards. I derive my inspiration from the experts in the field. I read their blogs and learn from them.
I hate it when I am required to prepare slides decks to present my findings to others. That’s a tough task. It is not possible to capture all the complexities into the slide decks. That is not my job. [informal interview, DigiBank]

On the other hand, the data science professionals who aspired to make a difference to the world by ensuring the consumption of their insights in decision-making tended to work closely with the business professionals. They spent a lot of time in understanding the pressing issues the business teams were facing and thinking how they could contribute to solving some of those issues. Data science professionals in this category were usually very concerned about the time and energy they put in developing a solution and wanted to see to it that the insights they produced were considered by the business professionals in decision-making. For them, success was measured in terms of the extent to which their insights were actually consumed in decision-making, the extent to which their projects got executed, and their impact on the bottom line.

These professionals tended to be more comfortable in prescribing insights to business professionals, but at times made compromises in inscribing their expertise in models and insights. The salient choices they tended to make while inscribing the expertise were typically catered to achieve the end state of making a difference. They involved the business professionals on the projects early on (even in the case of Pathway II projects). They constantly endeavored to anticipate the areas where the business professionals might want their help, and to strategize how and what to prescribe to them in such a way that their prescriptions got used. This orientation at times imposed a constraint on the way they could inscribe their expertise into models. A team leader explained what he aspires his team to achieve:

“The objective of our unit is to produce information that makes a difference in business decisions. It is important to understand their requirements and their pressing issues before spending too much time in exploring data.”[interview, DigiBank]

These data science professionals had an inherent fear of losing the arbitrage. To make sure that the business professionals remained dependent on them for making rational decisions, the data science professionals strived to focus on the problems that business professionals would have never conceived of before, and endeavored to offer such
solutions that the business professionals might not be able to understand thoroughly. As narrated by a business analyst:

“I am hired to bring in cutting-edge methods. Business teams can easily do simple analysis with small data. For that they don’t need me. My expertise is in bringing novel solutions that business managers can’t even understand.” [interview, FinBank]

3.5.4.2 Coordinating Expertise Within and Across Teams

As narrated in the sections of inscribing expertise and prescribing insights, data science as a profession hosts people with expertise in distinct functions, yet the choices those professionals make in enacting informing practices are intertwined and interdependent. This intertwined nature of choices required envisioning and anticipating the actions of other professionals within the data science team as well as in the business teams, in order to synchronize their own practices with the rest of the organization. The need for anticipation also demonstrates the epistemic interdependence within and across the teams (see Puranam et al., 2012). In this section, I elaborate on the implications of such interdependence on the nature of choices made by data science professionals in enacting the informing practices.

3.5.4.2.1 Within Team Coordinating Practices

Documentation Practices. Documentation played an important role in the informing practices of inscribing expertise. Documentation practices included the description of the models and analytical solutions developed, as well as the description of various data stored in the data warehouses (data dictionaries). While documentation was naturally beneficial for enacting the informing practices, it sometimes turned out to be a double-edged sword. For instance, on the one hand, having well-documented data dictionaries and codes of the previous models prepared by the data science professionals facilitated the predicting practices while inscribing expertise, as well as provided a good starting point for solving new problems inductively while prescribing expertise. A newly recruited data analyst explained his approach to getting started with exploratory analysis:

“The bank has been storing piles of data on their servers. However only tiny part of those data make it to the data marts. When I first joined the bank, I tried
to explore those data, however, could not do much due to lack of data dictionaries maintained for those data, and ultimately resorted to the curated data in data marts.” [interview, FinBank]

A well-documented data dictionary helped the newly recruited data analyst explore the data that could have been previously ignored during the funneling practices enacted by data engineers. In other words, the lack of documentation would impose constraints on the choices being made by the data analysts on where to look for interesting trends.

On the other hand, regarding the documentation about models and analytical solutions (codes), the implications were not straightforward. Unlike the normative documentation about standard operation procedures in typical banking organizations, the documentation about the codes and models in the data science units at my sites was more descriptive in nature. It recorded the modeling assumptions, justification of making those assumptions, and the meaning of the codes. Unlike the normative documentation prevalent in other organizing units, a descriptive documentation was adopted in the data science unit with an aim of not imposing the rules on the data science professionals and not telling them what to do; instead, it was aimed at providing them with the information of why a particular model was built the way it was built in past. However, my findings suggest that in practice, as the data science unit matured and accumulated the documentation of hundreds of models, the data science professionals started deriving patterns on what worked and what did not work in the past. So, as the data science unit got older, the descriptive documentation started functioning as an implicit normative documentation. For instance, a modeler explained:

*When I first joined, I started looking at the documentation to understand which types of models have been built in past and to solve which type of problems. It was very helpful to understand what could be acceptable and what could be not in this bank.* [informal interview, DigiBank]

Evidently, while the documentation provided a good starting point for conducting exploratory analysis, with the passage of time, it also imposed a taken-for-granted image of what the exploratory analysis should look like, thereby constraining the consideration set of the data science professionals.

**Coupling Practices.** Hosting professionals with expertise in data engineering, data analysis, reporting and visualization tools, modeling, and business analysis, the data
science units at my sites adopted idiosyncratic formal and informal team structures. The team structure resulted in tight or loose coupling among the professionals, which had implications for the choices being made in the informing practices.

For instance, in the case of FinBank, the data engineer and reporting analyst worked as one team which served the whole organization through their practices of *funneling the data* and *representing the present* while enacting the practice of inscribing their expertise into insights. This structure created a conducive environment for a tight coupling between the two. They used to consort with each other during the most formal as well as informal interactions. They knew and could handle more than 80% of each other’s work as well. This tight coupling influenced the choices of each other as well as the potential choices that other data science professionals could subsequently make.

In the funneling practice, the data engineer engaged in extracting, transforming, and loading those data from the servers that he considered the most useful in anticipation and in realization of the immediate needs of the reporting analyst for creating a meaningful representation of the present. The choices of the reporting analyst were naturally dependent on his anticipation of what the business needed to know, and his perception of what the business should know. Indirectly, the choices of the data engineer, while enacting the funneling practices, were more inclined toward the existing priorities of the business professionals as perceived by the reporting analyst. Unintendedly, the data engineer paid less attention to what data the modelers and data analysts could potentially use in the future in building novel models. As the data engineer narrated his choices:

“I need to prioritize updating these data in the data marts, as they are used in the senior management reporting dashboard prepared by my colleague. This is my business as usual. Other data are flexible, nobody will die if I delay it for a bit.” [interview, FinBank]

The two informing practices of funneling the data and representing the present became a part of the *business-as-usual* practices, which meant an ongoing pressure of delivering on time. The data engineer not only felt the time pressure of funneling the data from servers to data warehouses, but also the indirect time pressure of representing the present through reporting and preparing dashboards as he worked closely with the reporting analyst. Due
to such a tight coupling with the reporting analyst, the data engineer unintentionally resorted to funneling in those data that the business professionals demanded regularly in the form of reporting dashboards, leaving out the huge pile of data still stored in the servers that could potentially have been used by the data analysts and modelers if brought into the data warehouses.

**Socialization Practices.** The informing practices and the corresponding choices of data science professionals were also influenced by how they had been socialized with their colleagues during the early days of joining. For instance, in the case of FinBank, a new team member recruited for any role (in the data science team) typically worked on several ad-hoc projects involving tasks that cut across all types of informing practices before being allocated to a specific work practice on a full-time basis. Due to such a practice, the new members quickly learned the tricks of the trade and started reproducing the institutionalized informing practices. This quick learning of institutionalized practices left them with less inclination to explore and experiment with new ideas. They quickly started looking at the raw data through the eyes of their colleagues. For instance, a newly recruited data science professional narrated:

*During the early days, interacting with the colleagues is considered very important. This new recruit considers himself fortunate to work with almost everyone and help them in their projects by doing adhoc works of running models, curating data, tuning parameters, etc. ... this helped him develop a decent idea of how to get things done without reinventing the wheel. ... he knows which the data tables to use, the useful variables, what business problems are important, etc.*

[Fieldnotes, FinBank]

On the other hand, in the case of DigiBank, a new recruit was typically directly assigned to a full-time portfolio, and did not work on various ad-hoc projects with other colleagues in the team. The new recruits were typically imparted extensive business training for the business group they were supposed to support. For instance, a modeler narrated his experience of learning how to sell life insurance products when he joined the organization:

*“When I joined, I had an opportunity to undertake a proper training for the life insurance product with other relationship managers. I am still on contact with my batch mates. I am very proud of what I did. You need a very different mindset to understand business. Because of this training, I know life insurance*
“business domain much better than everyone else in my unit.” [interview, DigiBank]

Such a practice of socialization brought the data science professionals very close to their business counterparts, which influenced the choices they made in performing and prescribing rationality. With their enhanced business domain knowledge, they became experts in identifying the problems through selecting and translating those problems into the statistical narrative, but were less equipped to inscribe their expertise in models and insights through the practices of funneling the data, representing the present, and predicting the future. These data science professionals spent less time in the practices of inscribing expertise, but more time in first anticipating the business needs and then curating their sales pitch to the business to make sure that the insights they prescribed were acceptable to the business professionals.

3.5.4.2.2 Across Team Coordinating Practices

The practices of prescribing insights required data science professionals to coordinate with the business professionals in solving the business problems deductively or inductively. Depending on the pathway of problem-solving processes, the coordinating practices influenced the choices made by the data science professionals in inscribing expertise as well as prescribing insights.

Conforming to the Business Intuition. In the case of projects initiated by business teams through Pathway I, the data science professionals had little freedom to make choices for most of the informing practices. If plotted on a continuum of openness, most of the Pathway I projects leaned toward the close-ended side. In other words, the business professionals not only controlled the identification and formulation of the problems, but also dictated the predictor variables that the data science professionals should include in the models. With their years of experience in the banking domain, the business professionals had developed their intuitions about how the world worked, and they expected the data science models to reflect those intuitions. Even though the choice of predictor variables to be included in the models fell under the jurisdiction of the data science professionals’ work practices, the close-ended nature of the problems formulated by the business professionals, coupled with their intuition about the potential solutions,
left the data science professionals with little freedom in exercising that jurisdiction. In principle, the data science professionals had the freedom of making these choices, but exercising that freedom came at a cost of losing the project altogether. For instance, a team leader narrated:

> Our models are often combination of what product [business team] wants and what we think should go in the models. Sometimes, you have to go with the gut feelings of the product managers [business professionals], even if it does not make sense, in order to move forward with the project. When they [business professionals] come to us with their problems, they generally have an image of what the solution should look like. ... you can offer your expertise, but you can’t deviate too much from their imagined solution. [informal interview, DigiBank]

In these *Pathway I* projects, the data science professionals generally act as *executors* of the projects *driven* by the business professionals. The nature of context constrained the ability of data science professionals to inscribe their expertise in the models. If the data science professionals conformed to the business rationale, they ended up compromising on the practices of inscribing expertise into the models and insights. Alternatively, if they did not conform to the business rationale, and engaged in the practices of inscribing expertise based on the data and their skills in analyzing the data, they risked their prescribed insights being rejected by the business professionals.

On the other hand, in the case of projects under *Pathway II*, the data science professionals had ample freedom to make their own choices. They were able to decide where to look for the exploratory data analysis, which outcome to predict (dependent variable), which predictor variables to experiment with, and which algorithm to use. For instance, a data analyst enacting the *exploring* practice on a *Pathway II* project expressed:

> “We are now working on this [...] it’s a new project. It’s never been done before.... It gives me a lot of opportunity to work freely because I can have input in that. Because I know what the data is available. What we can extract from it and how can we use it. ... It’s like a path we create.” [interview, FinBank]

Overall, since most of the projects at my research sites fell under the *Pathway I* route, the occasions of constrained freedom to make choices were more common.
**Taking Shortcuts.** Apart from the freedom to make choices, availability of time was another factor that influenced the choices made by data science professionals in enacting informing practices, which created a paradox between prioritizing the outcome versus focusing on the process. The *Pathway I* projects were generally time-bound. The time available for the data science professionals to develop and deliver the solution was limited across all my sites. This was common for the open- as well as close-ended projects under *Pathway I*. In other words, even when the business professionals came up with open-ended problems and gave all the liberty to the data science professionals to make their choices in terms of the direction of the solution, the choice of independent variables, and the choice of algorithm for modeling, to realize that freedom, the data science professionals needed sufficient time, which was a rare resource in the *Pathway I* projects. A business analyst explaining the *Pathway I* projects narrated:

*In data science professionals’ perception, the business teams’ projects are always high-priority. They [business professionals] don’t care how data science professionals do it... they just need the immediate solution ... data science professionals often apply short-cuts to complete the projects, which they [data science professionals] consider to be okay, so far as our predictions are better than random guess.* [fieldnotes, FinBank]

Overall, finding themselves in the middle of a ticking clock, the data science professionals chose *shortcuts* to make their choices. These shortcuts included asking the business professionals to recommend the variables they think might be important for a particular problem (even if the business professionals gave the freedom to data science professionals to choose their own variables), re-using the existing models to avoid “*re-inventing the wheel,*” going with standard parameters values instead of spending time on hyperparameter tuning, and ignoring the variables not updated in the data warehouse by the data engineer (instead of collecting data directly from servers, by modelers), among others.

**Modeling for Interpretability.** Oftentimes, the practice of selling the insights under prescribing practices dictated the practice of modeling under the inscribing practices. Irrespective of the nature of projects (Pathway I or Pathway II), the data science professionals were required to sell their insights in such a way that was meaningful to the business professionals. One of the common approaches adopted by the data science
professionals in selling the insights was to present the insights in the form of implications for various customer segments. For instance, in the case of a project for automating the personal loans underwriting process while explaining the rate of predicted delinquency—failure to pay the outstanding debt—in the event of grant of the loan, the data science professionals would typically present the insights in the form of rate of delinquency for different age groups, different income groups, and different segments based on bank-assigned customer classification (e.g., customer banding from 1 to 5, with 1 meaning least profitable). Such a binning of insights into various customer segments worked very well in selling the insights as it resonated with the intuitive sense of the business professionals. Such a practice of binning the insights into customer segments for ease of interpretation by business professionals has long been institutionalized across the banks. A team lead explained the rationale:

You need to speak their language. If you want to convince them to use your insights in their decisions, you need present the insights that fits in their matrix. For this project, I present the predicted rate of delinquency in terms of customer profitability segments. As most of their [business professionals'] initiatives follow this segmentation. [informal interview, FinBank]

This orientation toward binning the insights into specific customer segments had significant implications for how the data science professionals inscribed their expertise into models. My findings suggest that the data science professionals often use the same bins used in representing insights (the classification that the business professionals normally use and understand) in building the models as well. They bin the continuous independent variables (e.g., income, age) into the same clusters and then treat those bins as categorical variables and input those categorical variables in the models. Unarguably, such a transformation of continuous variables into categorical variables is many a times required to model the non-linear relationships, but this particular approach of binning based on the predetermined categories oftentimes results in information loss. There are several alternative approaches of binning as well as there are alternative approaches of modeling non-linear relationships which are now available in the traditional analytical tools like SAS (e.g., Wu et al., 2018) as well as the newer open source tools like R and Python. Yet, many data science professionals at my sites adopted binning with pre-
determined categories in their modeling practices. One modeler explained a potential reason for such a choice:

“Most banks historically used SAS as their analytical tools, which continues till today. I have now moved on to using R, but I do remember that the earlier versions of SAS only had the provision of binning. Now they offer much more flexibility with alternative approaches to model non-linear relationship, but I guess many of us are stuck with the binning because ultimately while presenting the insights, we need to show the results in a way the product [business teams] can understand.” [interview, InvestBank]

3.5.5 Embracing the Paradoxes by Triggering Attention

Amid all the paradoxical constraints, there were some occasions where the data science professionals found ways to enact informing practices and perform rationality to their own satisfaction. The data science professionals at my sites did recognize the contextual factors imposing limitations on their freedom to make choices and on the time they could allocate in informing practices, especially in the case of Pathway I projects, which constituted the majority of all projects. One of the mechanisms they adopted was to trigger the attention of business professionals in such a way that it would fetch them more freedom and time, while still working on the projects initiated by the business professionals (Pathway I).

3.5.5.1 Triggering Attention through Representations

One way to trigger attention was through reporting, by representing an image of the world, that the data science professionals wanted to build a solution for. For instance, in the case of DigiBank, the data science professionals undertook several initiatives to help the business professionals across the functional teams (e.g., Liability group, Assets group, Digital Banking group) in automating their reporting dashboards (Pathway II projects) through a visualization tool, Tableau. The direct benefit of these projects was evident in establishing the position of the data science unit within the organization. For instance, a team leader explained during an informal chat:

Dashboard projects seem to the lowest hanging fruits for data science professionals. In the team leader’s experience working across various banks, he has seen reporting as a tedious task, and a perennial problem for business
professionals. By addressing this pain point, data science professionals gain their [business professionals’] trust. [fieldnotes, DigiBank]

These seemingly goodwill gestures from the data science professionals indirectly, albeit intentionally, influenced the attention of business managers. When the data science professionals reached out to the business professionals to automate their dashboards, which they had previously prepared by their in-house MIS executives (hosted within the business departments), the business professionals immediately agreed, as timely reporting of the correct information was one of the big pain areas for business managers. The business requirements for the dashboard automation projects were generally straightforward, as their main requirement was to get the dashboard at their desktops whenever they needed, with the same content as was in manually prepared dashboards (Excel-based reports). The data science professionals built the Tableau dashboards, which conformed to the requirements of the business managers, except a minor change. They added a small space to represent the performance of some business parameters which did not form part of the original dashboards. The business managers did not mind the addition of one or two new parameters, so far as they did not remove any important parameters that existed in the manual dashboards. The reporting analysts at times used this opportunity to add those parameters, for which they already knew of potential performance gaps and potential solutions to such gaps. Once the parameters (with gaps) were added to the automated dashboards, the business managers felt the need to respond as it triggered their problemistic search and the performance gap in that parameter now became part of their “agenda” (Simon, 1947). For instance, a reporting analyst described:

“If you want the business managers to take some action on your reports, you need to find a way to influence their business matrix. While preparing the dashboards for business, I often try to add few new parameters in the composite view. Sometimes it triggers action.”[interview, FinBank]

Having recognized the performance shortfall in the new parameter included in the dashboard, the business professionals reached out to the data science team (Pathway I), seeking their help in building a solution. Since the data science team had already envisioned the solution, and since this was a novel domain for the business professionals, for which they did not have much intuition about what the solution should look like, the
data science professionals were able to leverage all the freedom and time to perform rationality through their inscribing and prescribing practices, as they deemed appropriate.

3.5.5.2 Triggering Attention by Storytelling

Another mechanism the data science professionals adopted to trigger attention of business managers was *popularizing the successful models to invoke evaluative spillover*. When the data science professionals completed a particular inductive project under *Pathway II* for one business team (personal loans), they popularized the model by sharing the success stories, which then triggered the attention of the business managers from adjacent business teams (business loans). Such success stories helped the data science professionals gain recognition from senior management, triggering an indirect pressure on the business managers of other business units to adopt, or at least evaluate such advanced analytics models, for their business as well. For instance, the head of the data science unit, explained:

*Once they [data science team] implement a solution, they prepare a two-slide deck and share with all. One successful implementation usually resulted in 3 – 4 replications across other products [business teams]. [fieldnotes, DigiBank]*

For the senior managers, such successful implementations of data science projects worked as a tool to inculcate the competitive spirits between the business teams. Since the business teams competed among themselves for resource allocation and attention from senior management, they felt the evaluative pressures in implementing a state-of-the-art analytics solution, when their competing business team had implemented one. This resulted in an “evaluative spillover” (Bechky, 2020) among business teams, and hence they went to the data science teams to help them develop similar solutions as the other business teams. Again, since the data science team intentionally drove the attention of business professionals, they had an upper hand in dictating what would go in the model, and hence a chance to perform and prescribe rationality on their terms.

However, there was also a side effect of such attention triggers. Many data science professionals believed in maximizing the utility of the solution they had developed after months of hard work. They were driven by the *brute force* of advanced ML models and had the desire to promote such advance models as much as they could. With the inherent
preference for novel and high-tech solutions (Beane, 2019b; Elsbach & Stigliani, 2018), sometimes they replicated the models as-is without customizing for the specific business context of the respective business units.

3.6 Discussion and Theoretical Implications

In this field study of the data science function at three large Indian banks, I documented a paradox of rationality that the data science professionals face in their everyday informing practices. I first elaborated on their practices of inscribing expertise and prescribing insights, followed by highlighting the challenges they face in making the salient choices when the two practices are conceived together, and finally I described some of the strategies the data science professionals adopt to overcome those paradoxes.

The study documents the everyday work practices of data science professionals, by going beyond the discrete understanding of what data science is (Carter & Sholler, 2016; Faraj et al., 2018; Muller et al., 2019; Sharma et al., 2014) and by examining how data science professionals perform rationality in an organizational context (Cabantaus & Gond, 2011; Glaser, 2014). I find that data science professionals mainly engage in two types of informing practices (Schultze, 2000) through which they inscribe expertise and prescribe insights for rational decision-making. They inscribe expertise by enacting the practices of funneling the right data, representing the present, and predicting the future. They prescribe insights by enacting the practices of selecting the business problems/insights, translating the business problems into statistical narrative, and selling insights/insights-problem pairs to business professionals. In enacting these informing practices, data science professionals make various salient choices while acting as the custodians of rationality. The organizing context of problem-solving processes in which these choices are made imposes several constraints and at times leads to paradoxical tensions. Yet, sometimes data science professionals are able to break the boundaries of these constraints by triggering the attention of the business professionals. Overall, I find that data science in practice is much different from the one represented in the studies undertaken in discrete settings (Sharma et al., 2014); the informing practices of inscribing expertise and prescribing insights often impose paradoxical constraints on the ability of data science professionals in performing rationality. Figure 3.2 summarizes the findings.
In the following, I discuss some important implications and contributions for the literature.

### 3.6.1 Data Science: Inscribing Expertise and Prescribing Insights

This study contributes to the emerging literature on data science as a professional practice of inscribing expertise generating quantified insights for decision-making (Glaser, 2014; Steele, 2016). Literature suggests that the data science and analytics professionals working in a professional organization adopt the processes of prototyping, pinging, and contextualizing as they inscribe their expertise into the quantified models and tools, which are subsequently adopted by client organizations to make rational decisions. I extend this literature by documenting the informing practices of data science professionals when they work as “internal consultants” (Schultze, 2000), which blurs the spatio-temporal separation between production and adoption of insights and analytics tools. In particular, I offer two noteworthy findings. First, with the intra-organizational settings of my study, I observe several informing practices, which are less salient in the inter-organizational settings. For instance, as the data science professionals at my sites worked within the same organizations for which they were producing models, they needed to engage in a lot of “dirty work,” cleaning and wrangling data, before the data could actually be fed into models. The practices I document, in the form of funneling the right data and representing the present, are of particular importance from the perspective of intra-organizational settings. It is important to understand these practices due to the epistemic interdependence within data science teams as well as between data science and business professional teams (Puranam et al., 2012). Second, I find that data science professionals not only inductively solved novel problems, but also helped business professionals in addressing existing pain areas deductively. The inscribing and prescribing practices I observed for inductive problem-solving—funneling, representing, predicting (by exploring), selecting insights, and selling—resonate with the practices of probing, pinging, and contextualizing (Glaser, 2014) identified in the literature. However, the practices I document for the deductive problem-solving with problems initiated by business professionals take a slightly different shape involving selecting the problems, and translating the problems into statistical narrative. In addition, the context of deductive
problem-solving invariably influences the choices the data science professionals make across all the practices of inscribing expertise—funneling, representing, and predicting—as reflected in the paradoxical tensions between inscribing and prescribing practices while performing rationality.

Literature suggests that while inscribing expertise into models, data science and analytics professionals often face specific legitimacy challenges as they are producing knowledge to be consumed by others, and hence engage in various legitimizing practices—targeting, managed revelation, analogizing, technical incorporation, proofing, and political purification (Steele, 2016). While my study resonates with some of these practices identified by Steele (2016), I offer two additional insights. First, the orientation of data science professionals in engaging with legitimization practices might depend on their concept of rationality. My study documents that some data science professionals are driven more by the need to create an ideal representation of the world, as opposed to the need to influence the world through their actions. These data science professionals care less about the practices of targeting and managed revelation, and more on technical incorporation and political purification. Second, my study reports two mechanisms of using representation and storytelling as triggers for managerial attention (Ocasio, 1997) through which the data science professionals predate the need for legitimation. By engaging with these practices, the data science professionals manage to minimize the intervention from business professionals into their informing practices, hence managing legitimization ex-ante, instead of ex-post.

### 3.6.2 Data Science and Information Production

Few prominent scholars in the IS (Schultze, 2000), political sciences (Feldman, 1989), and organizational studies (Langley, 1989) have explicitly conceptualized and empirically examined the processes and practices of information production. I extend this stream of literature by examining the work practices of data science professionals. Early studies on analysts in organizational settings (Langley, 1989) implied that the major role of analysts was in catering to the demands of their managers, rarely contributing to decision-making by initiating projects on their own. Langley (1989) reported that in most cases (out of six interactions patterns identified) the requirement for analysis was initiated
by middle or senior line managers. In the rare cases when it was initiated by the analysts, none of it made it through in terms of implementation of the analysis in decision-making. My study adds two dimensions to this insight. First, my findings suggest that in the case of data science, the professionals do succeed in getting their insights consumed in decision-making, even for the projects initiated by them, albeit such instances are rare. Interestingly, the data science professionals sometimes manage to get their preferred projects initiated by business professionals by triggering their attention indirectly by the way of other data science projects, such as automating reporting dashboards and telling stories of successful data science projects for related products. These findings imply the possibility of data science professionals increasingly, though incrementally, gaining control of decision-making processes, which historically was considered to be the domain of line managers (e.g., in the Carnegie School tradition, March & Simon, 1958).

By examining the informing practices of various knowledge workers, Schultze (2000) marked an early point of departure in IS literature from “use of information” to “production of information” (p. 3). Schultze (2000) provides a succinct account of three informing practices including ex-pressing, monitoring, and translating enacted by the system administrators, competition intelligence analysts, and librarians, respectively. I extend our understanding of the informing practices of knowledge workers by documenting several additional practices in the context of data science. For instance, with the increasing piles of data being stored in organizations’ servers and corresponding reliance on AI-enabled analytics tools (Chen et al., 2012), the knowledge workers increasingly need to enact the practices of funneling the right data, representing the present to the business professionals in a way they can grasp, and predicting the future by engaging in various exploring and modeling techniques. Yet, these practices are not independent of the context in which they take shape and hence are influenced by various contextual factors.

3.6.3 Data Science, Technologies of Rationality, and Decision-making

My study provides a new direction for the literature on technologies of rationality in practice (Jarzabkowski & Kaplan, 2015), of which AI-enabled analytics tools are the latest manifestations (Pachidi et al., 2020). A large body of the emergent literature on AI
in practice has focused on the implications of adoption of AI-enabled analytics tools as well as technology artifacts on the work practices of the incumbent domain experts and business professionals (e.g., Aversa et al., 2018; Bader & Kaiser, 2019; Lebovitz, 2019). These studies directly or indirectly follow the framework of studying strategy tools-in-use by examining selection, application, and outcome of adoption of such tools (Jarzabkowski & Kaplan, 2015). In other words, these studies take the AI-enabled analytics tools as a starting point of their inquiry and as a result focus mainly on the consequences of quantification, paying little attention to how the tools and models are built in the first place (Glaser, 2014). By examining the informing practices of data science professionals as they inscribe their expertise in building models and generate insights for rational decision-making, I demonstrate an important, yet missing link in the literature. Building on the “biography of an algorithm framework,” (Glaser et al., 2020), my study demonstrates the role of data science professionals in crafting the biography of the models they build, which are in turn utilized by business professionals in decision-making.

My study also provides new directions for the organizational scholars interested in examining decision-making processes in organizations. Again, a large body of extant literature that has dominantly examined decision-making has focused on how managers process (or ignore) information in ways characterized as boundedly rational, socially situated, or politically motivated (e.g., March & Simon, 1958; March & Feldman, 1981; Tushman & Nadler, 1978). The term information is often used interchangeably with data, and hence treated as ready to be consumed in decision-making. By focusing mainly on the business managers, who are responsible for making decisions, these theories fail to recognize rational decision-making as a performative praxis (Cabantous & Gond, 2011) where not only the consumers of rationality (i.e., the business professionals), but also the prescriptors of rationality (i.e., the data science and analytics professionals) play an important role. My study provides an important milestone for bringing the analysts (Feldman, 1989; Langley, 1989; Schultze 2000) into our conceptualization of organizational decision-making.
3.7 References


3.8 Figures and Tables

Figure 3.1: Data Science Projects in Context of Problem Solving Processes
Figure 3.2: The Intertwined Informing Practices of Data Science Professionals
Table 3.1: Background of the Research Sites

<table>
<thead>
<tr>
<th>Particular*</th>
<th>FinBank</th>
<th>DigiBank</th>
<th>InvestBank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>26 years</td>
<td>16 years</td>
<td>26 years</td>
</tr>
<tr>
<td>Assets**</td>
<td>3,072</td>
<td>2,578</td>
<td>15,305</td>
</tr>
<tr>
<td>Deposits**</td>
<td>2,020</td>
<td>1,054</td>
<td>11,475</td>
</tr>
<tr>
<td># of Bank Branches</td>
<td>1,911</td>
<td>1,135</td>
<td>5,416</td>
</tr>
<tr>
<td># of POS Machines</td>
<td>115,793</td>
<td>89,148</td>
<td>872,912</td>
</tr>
<tr>
<td>Total Employees</td>
<td>30,674</td>
<td>22,973</td>
<td>116,971</td>
</tr>
<tr>
<td>DSU Team Size***</td>
<td>30</td>
<td>47</td>
<td>160****</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Digitization</th>
<th>Digital payments: &gt;80% retail transactions</th>
<th>Digital payments: &gt;30% market share of Aadhar / UPI payments</th>
<th>Digital payments: &gt;95% retail transactions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Digital onboarding: 75% retail liability, 47% personal loans, 24% cards</td>
<td>Digital onboarding: 40% deposits booked</td>
<td>Initiatives: over 200 APIs on partner/public API gateways, several industry first digital assets products, country wide digital innovation summits and hackathones, chatbots</td>
</tr>
<tr>
<td></td>
<td>Initiatives: Blockchain for remittances</td>
<td>Initiatives: underwriting automation, integrated value chain for vehicle loans, chatbots</td>
<td></td>
</tr>
</tbody>
</table>

Note:
*All figures as of March 31, 2020 (end of financial year 2019-2020)

**Billions of Indian Rupees

*** Employees in Data Science Units, inclusive of the staff administering campaigns.

****InvestBank had two separate data science units, the one for marketing analytics and the other for risk analytics. My study participants belonged to the marketing analytics unit.
Table 3.2: Summary of Data Collection

<table>
<thead>
<tr>
<th>Data Source</th>
<th>Description</th>
<th>FinBank</th>
<th>DigiBank</th>
<th>InvestBank</th>
</tr>
</thead>
<tbody>
<tr>
<td>On-site Observations</td>
<td><em>Shadowing</em> the data science professionals to observe their work practices.</td>
<td>Shadowing 1 modeler and 1 data analyst.</td>
<td>Shadowing 1 data analyst, 1 modeler, 1 team leader and 1 team leader.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Attending formal and informal <em>meetings</em>, among the data science professionals within the team, as well as between the data science and business professionals across the teams.</td>
<td>7 formal meetings within team, 2 formal meetings across teams, and several informal meetings.</td>
<td>9 formal meetings within team, 4 formal meetings across teams, and several informal meetings.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Conducting <em>real-time interviews</em> including brief (10-15 minutes) and long (60-70 minutes) conversations.</td>
<td>8 long interviews, and several brief conversations.</td>
<td>14 long interviews, and several brief conversations.</td>
<td></td>
</tr>
<tr>
<td>Overall Observations</td>
<td></td>
<td>200 hours</td>
<td>400 hours</td>
<td></td>
</tr>
<tr>
<td>Semi-structured Interviews*</td>
<td>Semi-structured interviews with data science and business professionals. Several informants were interviewed twice to ask the follow-up questions that emerged basis observations and other real-time interviews.</td>
<td>15 interviews with 10 data science professionals (2 modelers, 2 data engineers/reporting analysts, 3 team leaders, 2 data analysts, 1 visualizer), and 2 semi-structured interviews with business professionals.</td>
<td>34 interviews with 20 data science professionals (5 modelers, 3 data engineers, 3 reporting analysts, 4 campaign data analysts, 5 team leaders), and 5 semi-structured interviews with business professionals.</td>
<td>10 interviews with data science professionals (8 modelers, 1 senior modeler, and 1 team leader).</td>
</tr>
<tr>
<td>Archival Records</td>
<td>Various archival documents as well as information artifacts were reviewed during the study, mostly during the idle time, viewed on the computer screen.</td>
<td>Algorithmic codes (SAS, Python), vendor algorithms, model outputs, and slide decks.</td>
<td>Emails, slide decks, consultant proposals/reports, organizational chart, minutes of meetings, algorithmic codes (R), automated dashboards (Tableau), and model documentation.</td>
<td>Standard operating documents, and process manuals.</td>
</tr>
</tbody>
</table>

**Note:**
*In addition, 8 semi-structured interviews with various data science professionals working in other organizations (apart from the three research sites) across industries were conducted during the early phase of the study to understand the phenomenon better, mostly during the stage of site identification.*
<table>
<thead>
<tr>
<th>Informing Practice</th>
<th>Enacting By</th>
<th>Input: (Raw) Data / Artifacts</th>
<th>Activities &amp; Technologies</th>
<th>Salient Choices</th>
<th>Output: Information Artifacts</th>
</tr>
</thead>
</table>
| Inscribing expertise through funneling | Data Engineers                            | Raw data flowing from various systems including core banking system, point of sale system, digital banking channels | **Activities:**  
  – Process (raw) data using Extract, Transform, and Load (ETL) functions  
  – Update Data Warehouse / Marts at regular frequencies  
**Technologies:**  
  – SAS, SQL, Hadoop  
  – Filtering out the noise from signal and selecting important and relevant data to be funneled into data warehouses and data marts | Transformed data stored in data warehouses and data marts                                                                 |                                                                                                                         |
| Inscribing expertise through representing | Reporting Analysts / Visualization Experts | Data stored in data warehouses / data marts              | **Activities:**  
  – Prepare reporting dashboards  
  – Refresh dashboards at specific frequencies (e.g., daily)  
  – Modify dashboards by including/ excluding parameters, changing evaluation criteria  
**Technologies:**  
  – Power BI, Tableau, MS Excel  
  – Representing meaningful information in a way that can business professionals can visualize and interpret | Macro enable dashboards (e.g., Excel sheets), reports in the visualization tools (e.g., Tableau) |                                                                                                                         |
| Inscribing expertise through explorative predicting | Data Analysts                            | Data stored in data warehouses / data marts              | **Activities:**  
  – Explore and analyze data to construct trends and predict relationships, by systematically querying the data and envisioning potential scenarios  
**Technologies:**  
  – SAS, SQL  
  – Predicting the future by extrapolating the trends by factoring appropriate plausible scenarios | Summary tables and charts shared over emails or slide decks                                                               |                                                                                                                         |
<table>
<thead>
<tr>
<th>Role</th>
<th>Activities</th>
<th>Technologies</th>
<th>Summary tables and charts shared over emails or slide decks</th>
</tr>
</thead>
</table>
| Modelers                           | Data stored in data warehouses / data marts                                                   | Activities:  
− Use various statistical and computational tools to model the real world to predict some outcome, given the independent parameters  
Technologies:  
− Python, R, SAS  
− Predicting the future by choosing appropriate modeling techniques, on appropriate data and variables, using appropriate algorithms                                                                                           | Model accuracy matrices (e.g., confusion matrix) and Model Predictions (e.g., list of accounts that are predicted to attrite) |
| Business Analysts                  | **Within Team:**  
Model outputs of modelers, data extracts from data analysts  
**Across Teams:**  
Business problems to be solved with the help of data science  
Activities:  
− Select pursuable business problems for deductive problem-solving and sellable insights for inductive problem-solving  
− Translate business problems in statistical narratives for deductive problem-solving  
− Sell the insights paired with business problems as solutions to business professionals  
Technologies:  
− Emails, Slide Decks, Word Processors  
− Identifying the right business problems and right insights that will provide opportunity to perform rationality  
− Adding value through expertise and experience while translating  
− Pairing the insights with problems in selling                                                                                           | Summary tables and charts shared over emails or slide decks |
3.9 Appendices

3.10 Appendix B1: Ethics Approval

Dear Professor Ngai Su,

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed and approved the WREM application form for the above mentioned study, as of the date noted above. NMREB approval for this study remains valid until the expiry date noted above, conditional to study submission and acceptance at NMREB Containing Ethics Review.

This research study is to be conducted by the investigator noted above. All other required institutional approvals must also be obtained prior to the conduct of the study.

Documents Approved:

<table>
<thead>
<tr>
<th>Document Name</th>
<th>Document Type</th>
<th>Document Date</th>
<th>Document Version</th>
</tr>
</thead>
<tbody>
<tr>
<td>Email Recruitment Script</td>
<td>Recruitment Materials</td>
<td>01/Apr/2019</td>
<td>1</td>
</tr>
<tr>
<td>Interview Guide for Digitization and Decision-Making Project</td>
<td>Interview Guide</td>
<td>01/Apr/2019</td>
<td>1</td>
</tr>
<tr>
<td>LOI and consent for face to face interview v2</td>
<td>Written Consent/Assent</td>
<td>09/May/2019</td>
<td>2</td>
</tr>
<tr>
<td>LOI and consent for observations v2</td>
<td>Written Consent/Assent</td>
<td>09/May/2019</td>
<td>2</td>
</tr>
<tr>
<td>Observation Guide</td>
<td>Participant Observation Guide</td>
<td>01/Apr/2019</td>
<td>1</td>
</tr>
<tr>
<td>Verbal Recruitment Script</td>
<td>Oral Script</td>
<td>01/Apr/2019</td>
<td>1</td>
</tr>
</tbody>
</table>

No deviations from, or changes to the protocol should be initiated without prior written approval from the NMREB, except when necessary to eliminate immediate hazard(s) to study participants or when the change(s) involves only administrative or logistical aspects of the trial.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Human Subjects (TCPER), the Ontario Personal Health Information Protection Act (PHIPA), 2004, and the applicable laws and regulations of Ontario. Members of the NMREB who are named as investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the EREB. The NMREB is registered with the U.S. Department of Health and Human Services under the IRB registration number IRB 00000091.

Please do not hesitate to contact us if you have any questions.

Sincerely,

Kelly Peterson, Research Ethics Officer on behalf of Dr. Randall Graham, NMREB Chair

Note: This correspondence includes an electronic signature (validation and approval via an online system that is compliant with all regulations).
3.11 Appendix B2: Interview Protocol

Common Questions

Background
Please tell me about your role and experience in the organization.
Please tell me about your professional and educational background.
Please tell me a little more about your experience before joining the company.

Department Strategy
Please tell me about the department’s overall history, size and structure.
How would you describe the department’s strategy and role on the organization?
How did the department’s orientation evolve over the years?
Which are the other departments that use the output of your department in organization level decision-making?

Data / Information Characteristics
How do you define / describe data?
How do you define big data?
How is big data different from other sources of data?
What are the different types of data you (organization) collect?
Do you specialize in analyzing a specific type of data? Describe.
How do you define / describe information? Are information and data the same or distinct? How?
Has big data changed the decision-making processes in organization? How?

Success Measures
Could you describe, in your opinion, two successful and two unsuccessful projects undertaken by the department?
What were the key success factors of these projects?
What were the challenges for these projects?

Questions for Data Science Professionals

Analysis Process
Could you describe the process you follow step-by-step starting from data collection to production of analytics output?
What is the most challenging part of this process?
What is the most exciting part of this process?
What are the types of decisions you need to make in the whole process and what are the decisions inbuilt in algorithms?
How do you make those decisions?
Could you change the code of algorithms to change the inbuilt decision logic? Do you use learning algorithms (ML)? What part they learn and what part is still inbuilt?
Analytics Output
How do you generally present the results / output of your data analytics?
Do you use separate visualization tools to present the output?
How do you decide on a particular approach / particular tool to present the output?
How do you ensure the user (e.g., product team) of your analytics output understands the same clearly?
Do you also share the data along with analytics output? Do you ever get such requests from the users (e.g., product team)?

Questions for Business Professionals

Information Processing
How do you use the insights shared by data analytics teams in your decision making?
What types of decisions are driven by big data analytics vs what type of decisions are excluded from this? Why?
Could you describe the decision-making process, step-by-step, for representative examples decisions of each category?
The data-driven decisions, how you used to make these decisions in absence of big data analytics, a few years ago? What has changed?
Chapter 4

Essay 2B. The Rhetoric and Reality of Data Science: Prevalent Myths and Lessons for Practitioners

4.1 Abstract

Data science is rapidly emerging as one of the most sought-after professions among information systems practitioners. Naturally, this rapid popularity has led to a lot of hype and rhetoric. For senior managers and leaders, it is important to demystify the hype and develop a deeper understanding about the profession to be able to successfully lead their organizations towards data-driven decision-making. In this paper, we highlight the rhetoric and myths around data science and carve out important lessons for senior managers, leaders, and data scientists in maneuvering their journey toward data-driven decision-making.

Keywords: Data Science, Machine Learning, Myths, Rhetoric

4.2 Introduction

Data science has emerged in recent years as an important corporate activity and a distinct profession (Davenport & Patil, 2012). As companies have scrambled to gain a competitive advantage through analytics (Davenport et al., 2020; Iansiti & Lakhani, 2020), data scientists have become highly sought after (Veeramachaneni, 2016). Incumbent firms in many industries have made significant investments in creating their own data science capabilities, often by establishing their own data science or business analytics teams. These new teams seek to apply statistical and other analytical techniques to business challenges by taking advantage of recent advances in data-crunching computer power – through application of so-called “big data” approaches – and also leveraging advanced techniques made possible by AI and ML. The objective: more

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17Since this essay is written for a practitioner audience with an aim of publishing in a journal read by practitioners (MIT Sloan Management Review), it is purposely written in a practitioner-oriented language, as opposed to the academic language in the other essays.
evidence- and insight-based business decisions. In many cases, however, these major investments have fallen short of achieving the benefits promised (Bean & Davenport, 2019). Substantial analytics capabilities have been acquired, but many companies have not yet been able to connect the dots to achieve real business value consistently.

Our research has uncovered at least a few of the reasons why. Through in-depth study of the data science activities of leading Indian banks, we have identified five common problems—all of them non-technical—that can prevent data science efforts from realizing actual business value through the case vignettes from our research. Although we studied the financial services industry, an examination of the five vignettes below should make it clear that they are not unique to financial services. For each vignette, we elaborate on the rhetoric, reality and recommendations for practitioners.

The essay is organized as follows. First, we discuss the definition of data science and the emergence of data science as a new profession. Second, we explain and illustrate the vignettes organizations face in generating business value from data science initiatives and provide recommendations to alleviate such problems. Finally, we conclude the paper by summarizing key implications.

4.3 The Emerging Profession of Data Science

A basic description of the occupation of data science is a prerequisite to understanding the implications for decision-making. “It is … impossible to open a popular publication today, … and not run into a reference to data science, analytics, big data, or some combination thereof” (Agarwal & Dhar, 2014). Academic institutions as well as industry incumbents have been equally contributing to this exponential discourse around data science in the last few years. Several universities have recently their data science programs and curriculums (albeit some have just renamed their existing programs in statistics). For instance, the University of Michigan made an announcement in September 2015 about the launch of a $100 million Data Science Initiative. Harvard, MIT, and several other high status institutions have announced similar initiatives. Parallelly, the demand for data scientists has increased in the industry as well, and was
labeled the sexiest job of the 21st century (Davenport & Patil, 2012). The trend is not only prevalent among technology leaders but also among incumbent firms in other industries.

Intuitively, several elements of the increasing prominence of data science seem more rhetorical than real, and hence there are several debates among academicians about what actually constitutes data science. Some experts believe data science to be more rhetorical and a relabeling of statistics or computer science, while others consider it to be more real and a child of several fields including statistics and computer science (Blei & Smyth, 2017; Donoho, 2017).

Notwithstanding the debates, for organization theorists and IS scholars alike, it is important to understand how organizations are grappling with this so called new profession of data science. As, “around all the hype [...] there is a ring of truth: this is something new” (Schutt & O’Neil, 2013). In addition to re-branding, recently, several large organizations have also incorporated their new data science units and recruited professionally trained data scientists. These units are different from the typical MIS or BIU departments the banks traditionally had. This wave of data science has made organizations consciously think toward being data-driven in decision-making. Next, we describe five common problems organizations face in their quest to become data-driven and to generate business value from their data science initiatives using five case vignettes based on our research and we also provide recommendations to avoid such problems.

4.4 The Rhetoric and Reality of Data Science

4.4.1 Vignette I

4.4.1.1 The Myth and the Rhetoric

“I have got a hammer, so every problem looks like a nail”

Karl Broman, Professor of Statistics at the University of Wisconsin, suggest in his blog that Data Science is statistics: “when physicists do mathematics, they don’t say they’re doing number science. They’re doing math. If you’re analyzing data, you’re doing statistics. You can call it data science or informatics or analytics or whatever, but it’s still statistics.” https://kbroman.wordpress.com///data-science-is-statistics/
Hiren\textsuperscript{19}, a newly recruited data scientist in one prominent bank, is the kind of data wizard that every organization covets for its analytics group. He has mastered state-of-the-art ML algorithms as part of his studies at a prominent international university. He’s naturally curious and a true believer in the wonders that data science can accomplish in business. But Hiren is especially taken with one particular algorithm, the k-nearest-neighbors algorithm, which is especially useful for classification purposes, to identify clusters of similar data entities. As he explained in an interview, “I have applied k-nearest-neighbors to several simulated datasets during my studies, and I can’t wait to apply it to the real data soon.”

He didn’t have to wait very long. A few months after joining the bank, Hiren started working with the checking accounts product team to identify profitable industry segments within their accounts portfolio. Not surprisingly, he recommended use of the k-nearest-neighbors algorithm to solve the problem. He input 33 already-defined segments, applied the algorithm, and came up with a clear recommendation to focus on two especially profitable segments.

But he was surprised when his data-based conclusion underwhelmed the checking account product team. Why? They already knew about these industry segments and how profitable they were. They had arrived at that conclusion using mere back of the envelope calculations. The k-nearest-neighbors algorithm represented far more firepower than was necessary to arrive at this conclusion – it was like using a guided missile when a pellet gun would have sufficed.

Another situation in a different bank provides an example of a variation on the same problem: Aarti, the personal loans product manager at the bank, with help from Kuntal, a data scientist, successfully automated personal loan underwriting using an algorithm based on ML techniques. The algorithm was able to automate the whole of the underwriting process for 50\% of loan applications, leaving only the other half to be

\textsuperscript{19}All the references to individuals and banks are pseudonymized to protect the confidentiality.
accomplished though human intervention, a major productivity improvement. Aarti’s supervisor, Vrinda, the business head for unsecured assets, was impressed. She proposed automating business loan underwriting in the same way; Kuntal, riding a wave of data science success, was only too happy to help. Working with Ashit, Aarti’s peer product manager on the business loans side, Kuntal implemented the same algorithm for business loans.

But for business loans, it didn’t work nearly as well. Even though personal and business loans both resided under the umbrella of unsecured loans, there were differences between the two loan types that mattered. Personal loan decision-making centered on individual creditworthiness as determined by a customer profile based on payment history, demographics, and transaction patterns. Business loan decisions, however, also needed to take into account the market situation and risk exposure of a business. Also, with personal loans, the bank had several data sources to use to triangulate and profile customers; the profiling for businesses, in contrast, was not as simple: a lot of information that had historically gone into business loan underwriting had come from face-to-face interaction between underwriters, relationship managers, and customers. Most of that was not written down anywhere, so it could not easily be input into an algorithm (even if the algorithm had been designed to account for that kind of info). As a consequence, the algorithm underperformed badly in the business loan department.

In both of these examples, the problem is similar. A solution technique is applied without enough consideration of the nature of the problem and its context. In the first instance, the problem was relatively simple and did not justify such an elaborate data science approach to solve it. In the second, enthusiasm for a data science solution caused its misapplication in an apparently similar but actually importantly different context. In both instances, the failure to achieve business value resulted from infatuation with a solution concept – a hammer in search of nails to pound (Maslow 1966).
4.4.1.2 The Reality and the Lessons

In both of these cases, the people involved corrected course and had subsequent success with challenges closely related to the ones in which their data science approaches had at first misfired.

After spending a few more months developing a deeper understanding of the business requirements and establishing his identity in the organization, Hiren came up with a new recommendation: use the \textit{k-nearest-neighbors} algorithm at the customer level instead of industry segment level. This was a much better fit. He could classify customers into different segments and then, with the help of the product team, interpret and assign appropriate labels to customer segments. This turned out to be a very fruitful exercise. The product team had not in the past thought about customer segments in this way; now they were able to target a whole set of new customers which had been untapped earlier, which had a huge potential. They were still using Hiren’s favorite algorithm, but now it was in an appropriate context.

Kuntal also stepped back after his failure and took time to achieve a better understanding of the business context. Unlike Hiren, though, Kuntal changed his solution approach. He replaced the sophisticated ML approach he had used for personal loans with a simpler statistical approach to business loans that would provide decision support for human underwriters. Decisions still needed to be made by human underwriters because there was so much tacit knowledge that needed to be considered in the decisions that would be hard to input into an automated algorithm. Even without automation, this better-suited solution helped cut underwriters’ time to process a business loan application by 40%, a business gain almost as great as from automating personal loan decision processes.

It might seem surprising that this problem is as common as it is. After all, it is not exactly rocket science to observe that solutions are likely to work best when they are derived from a careful understanding of the nature and context of the problem. The problem, our research suggests, is that data science solution techniques \textit{do} come across to
lay managers as rocket science – solution approaches that are categorically better, regardless of context, than what has come before.

However, as our case vignettes demonstrate, they are not necessarily better all the time. Though powerful, data science approaches do not negate the importance of understanding the problem and its context. All tools – even rocket science tools – need to be applied appropriately, not anywhere and everywhere just because they are powerful. The best corporate data science efforts, then, are those that emphasize leading with a careful analysis of the problem and avoiding becoming infatuated with particular solution concepts.

The caveat to this qualification, however, is that leading with careful analysis of the problem should not mean being bound by historical mindsets and other organizational “baggage.” Data science is a way of conceiving problems from a different direction. So, it may involve reformulating problem. It needs to be free to do that. That is a big part of its potential for business value.

Here is some specific advice that we can derive from our study, related to this problem:

- Treat each problem as a distinct challenge and start afresh;
- Take time to first understand the problem before choosing a solution approach;
- Consider the possibility that the problem can be solved by simpler means and thus may not need data science modeling;
- Develop the best solution for a particular problem and apply it accordingly;
- Keep in mind that due to the complex nature of most businesses, most solutions will not transfer without modifications from one context to even seemingly similar contexts;
- Though it is important in any data science exercise to pay heed to the problem, do not extend leading with understanding of the problem into allowing historical attitudes or other “baggage” to impose constraints for no reasons other than historical practices; and
• In promoting data science approaches within the organization, emphasize the analytical approach rather than over-relying on specific solution concepts. Bearing in mind the human tendency to become fixated on the jazziness of a new technology; effective application of data science requires avoiding this kind of fascination with the new bright, shiny object.

4.4.2 Vignette II

4.4.2.1 The Myth and the Rhetoric

“Infusing bias while attempting to remove it”

Pranav was developing an algorithm to help the underwriters who granted secured business loans to small and medium enterprises (SMEs). The objective was a tool to keep underwriters from missing important decision parameters and help them avoid potential subjective biases within the underwriting process. With the help of the SME business teams, Pranav obtained all the Credit Approval Memos (CAMs) for loan applications processed over the last 10 years in the bank, which he then analytically compared with the current financial health of each of the borrowers. The idea was to identify parameters correlated with delinquent behavior. Within a couple of months, Pranav thought he had a highly accurate model; his manager presented it to the business team, which approved it for implementation.

But after just six months of use, it became clear that the tool was not working. Rates of delinquency were actually higher after the tool was implemented. Perplexed, senior managers assigned an experienced underwriter to work with Pranav to figure out what was wrong.

The epiphany came when the underwriter discovered that the input data came from CAMs. What the underwriter knew that Pranav hadn’t, was that CAMs – the source of data for the model – were prepared only for approved loans. Loan applications rejected by underwriters were not present at all in the input dataset. Predicting delinquent behavior without data from loan applicants most likely to become delinquent constituted
a huge selection bias in the model. This bias had led Pranav to drop an important parameter – numbers of checks returned – due to low information value. It had low information value because it had low variance – not surprisingly, there were very few instances of returned checks in the set of borrowers that underwriters had determined to be low credit risks.

4.4.2.2 The Reality and the Lessons

The technical fix in this case was easy: Pranav acquired and included data on rejected loan applications. The checks returned parameter took on greater variance and became important in his model, based on the new, no longer selection-biased data set. The tool began to work.

The bigger problem is how to discern the bias upfront, so that it does not creep into the model in the first place. Such hidden biases are one of the most challenging issues that affect analytical models in the age of AI. The technical sophistication of the methods makes them not very transparent. Lay people, who well understand context, or even analytics experts themselves, cannot easily see into the “black box” to see how output are being arrived at.

It should be clear from this example, though, that if an underwriter had worked more closely with Pranav early in the project, he would have been much more likely to point out the bias in the CAMs data source. As a well-trained data scientist, Pranav realized instantly when he learned that CAMs represented only approved loans that there was a serious problem. He just hadn’t known enough about CAMs. The obvious suggestion is that data science initiatives need to be proceeded by a robust process for analyzing the business context, a process that draws data scientists and business domain experts together to work as a team.

Based on this case (and others like it), we derive from our study the following specific advice:

- Standard data science approaches should include, on their front end, a problem context analysis that includes data scientists and business domain experts. In
particular, the list of predictor variables included in a model should be jointly scrutinized by data scientists and business experts;

- Business managers need to put effort into understanding data science imperatives intended to avoid constructing flawed models. They should attempt to understand the rational choices made by data scientists, including the logic behind choices of an analytic method, of prediction variables, and specific datasets;
- Similarly, the data scientists should put effort into understanding the business context of a problem, especially the definitions of variables and origins of datasets. By mastering some of the details of the business, the data scientist can avoid potential biases, including some cognitive biases that might be embedded in business decision makers’ mindsets; and
- Business leaders also need to align their incentives and rewards structures for data scientists and domain experts to promote a culture of questioning assumptions, which will help “deodorize the data” (Ransbotham, 2017) that goes into analytics models.

4.4.3 Vignette III

4.4.3.1 The Myth and the Rhetoric

“A good solution but at the wrong time (timing matters)”

At another bank, Kartik, a data scientist, developed a savings account attrition model. It took him about a month to develop an initial version using a state-of-the-art algorithm. Though sophisticated, the model at first had only moderate accuracy. It took three more months to fine-tune the model to achieve a high level of accuracy. When Kartik finally shared the insights with the savings account product team, they really liked his findings and approach but could not implement anything to address the model’s predictions because they had already finished with the annual budgeting cycle. There was no point at that time for any business leader or unit to take up sponsorship of a project based on Kartik’s model. Though they were impressed by what he had accomplished,
operational managers had already moved on from formulating new projects, turning their attention elsewhere.

Eager to avoid the same problem again, Kartik presented his findings to the product team in the following year before the budgeting cycle began. But he met with another roadblock. For that particular year, the business team had a mandate from the senior management team to focus on savings account acquisition. All projects in this year needed to connect to account acquisition objectives. Moderating attrition took a backseat. Once again, Kartik could not find a business sponsor for a project that acted on the findings and insights within his model.

Finally, in his third year of trying, Kartik had better luck. There was a change in the savings account product team leadership, and the new business leader was ready to sponsor an analytical solution based on insights from Kartik’s model. Though Kartik was pleased that his data science approach was finally gaining traction within the organization’s activities, he still expressed frustration: “Despite [my] having spent four months in perfecting the model, the business team did not even look at it for two years. Now they want to implement it, but the model has already decayed and hence I will need to build it again!”

4.4.3.2 The Reality and the Lessons

Like the first problem, this one is a matter of poor fit between data science activities and the reality of the business context. The fix, then, has to do with creating better linkages between data science activities and the initiatives and systems that are at the heart of how the business is run. We can see from this example that Kartik’s data science activities would have produced more business value sooner if they had been coordinated with the budget cycle and driven by strategic priorities. If there had been a more effective linkage between strategy and specific data science activities, Kartik might have been working on a different problem and a different model, especially in the second year when senior management set account acquisition as a strategy priority.
Based on our research, we conclude that data science practices need to be embedded within a process framework that takes into account operational business cycles and, especially, overall business strategy. Data scientists ought, for the most part, to concentrate their efforts on the problems deemed most important by business leaders (O’Toole, 2020). The irony, in this example, is that Kartik spent months perfecting a model that was no longer relevant to the priorities that the business had set for itself by the time he was finished.

However, as with problem 1, there is a caveat embedded in the fix to this problem also: Sometimes data science insights lead to unexpected conclusions that should be brought to the attention of senior leaders and should perhaps even govern future strategy making. The problem here is one that afflicts innovation whenever it occurs within organizational contexts: It is difficult for ideas that are original and do not resemble past valuable ideas, or do not fit with current tendencies within the organization to exploit current business opportunities, to get the attention of managers. As with the fix for problem 1, there is a line to be walked here. If a data science conclusion is a bad fit with current priorities and systems but seems to be of great importance to the company, its strategy, or operating priorities, then data scientists should push hard against the tide of organizational initiatives and systems, to gain attention for their important finding.

The following is some specific advice that we can derive from our study, related to this problem:

- Timing is important to the acceptance of data science-based projects. To be effective, data scientists need to think explicitly about how to insert their insights and conclusions into organization discourses at appropriate times;
- Data science activities should have an explicit role in strategic and operational processes and systems. This might require companies to revise their existing processes and systems, to take data science activities into account;
- One way to ensure synchronization with business priorities and systems is for data scientists to frequently engage with business stakeholders, to create an awareness of
what data science activities are working on, and to obtain feedback that will help improve and course-correct data science solutions;

- Data scientists should avoid long periods of time when they are perfecting models without interacting with business stakeholders. It is better to bring beta models into the conversation with business leaders sooner, in more of an iterative, agile approach. Models can then be perfected later with the benefit of inputs from business leaders; and

- In the rare situations where a data science activity produces a critical insight that suggests that the business should change course, data scientists need to work hard to gain attention for that insight, even if the insight is not in line with existing priorities and operating cycles.

### 4.4.4 Vignette IV

#### 4.4.4.1 The Myth and the Rhetoric

"Not Realizing that the Medium is the Message"

Sophia, a data scientist at her bank, developed a model that she built into a recommendation engine. This recommendation engine used customer profile information to suggest a banking product that was not currently being used by the customer, but that was very likely to be chosen by the customer if it was presented to her or him. Recommended products could be in any category: savings, loans, cards, or investments. Initial testing of the model on a historical data set suggested that the model would predict customer behavior with high accuracy.

With help from the marketing campaigns team, Sophia implemented the model in the form of a digital recommendation engine, that would send out recommendations to customers through the bank’s mobile wallet app, its internet banking site, and also through emails. After the implementation, they had predicted a good turn around of customers inquiring about the product.
Despite the earlier tests, however, customers’ uptake of the new product suggestions was much lower than expected. With the help of telemarketers, Sophia surveyed a sample of customers who did not purchase the new products even though the model predicted with high probability that they would. Very quickly, an answer emerged: many customers had doubts about the credibility of recommendation coming from apps, websites, and emails. Although digital channels had seemed the natural way to distribute offers from her digital recommendation engine, it did not really work for customers.

Trying to determine whether there was a solution for this problem, Sophia visited some bank branches, interacting with customers with the help of relationship managers (RMs). She was surprised to see how much trust the customers seemed to place in the RMs. A few impromptu, informal experiments later, she was convinced that customers were much more interested in the recommended products when a trusted RM was involved in presenting them.

There was nothing wrong with the model, Sophia realized. The problem was the channel through which the recommendations were communicated. Returning to her office, Sophia met with the senior leaders in the branch banking team and proposed relaunching the recommendation engine as a tool to support product sales through the RMs. The model and the recommendations would remain the same, however, instead of the direct digital channels, it would now be the RMs who presented the products to customers during their regular meetings. Redesigned in this way, this data science initiative became a huge success. It was especially successful, as it turned out, for investment products.

4.4.4.2 The Reality and the Lessons

The difficulties Sophia encountered in this story suggest the wisdom of paying attention to how the outputs of a data science model will be used. Just as a great product idea requires a lot of further thought about how it should be commercialized, so a great data science model needs careful consideration of how to best integrate its outputs into day-to-day business. As Sophia learned, the data scientist’s responsibility for the
effectiveness of a model does not end with proof that the model is predictive. The steps Sophia took to figure out why the model she had so much confidence in was not working set a good example, but we suggest that such analysis should take place as a natural extension of every data science initiative; if this had been a planned part of the implementation process at Sophia’s bank, she might have discovered the right channel for distribution of her model’s recommendations at the outset.

The following is some specific advice that we can derive from our study, related to this problem:

• The process framework for data science initiatives should extend beyond the successful development of a data science model and its implementation within a digital platform, to considerations of how the outputs of a data science model will be used, and by whom: what channels resulting information should be distributed through, and which constituencies have the right roles, authority, and incentives to maximize the value of the data science-generated information;

• When it comes to consumption or deployment of the outputs of a data science model, digital is not always better. Just as people can become transfixed by the rocket science elements of data science, so can they become infatuated with digital as the right way to move into the future. This is not always the case; the potential of digital is dependent on country, industry, and product contexts (Carter, 2019; Chakravorti & Chaturvedi, 2019). Data science can be effectively executed through non-digital channels as well. In India, which is considered one of the leading FinTech economies, most of the large and technology-savvy banks still source only 5% to 10% of their business through digital channels. Traditional channels, such as brick-and-mortar branch banking remain very important;

• Data scientists should think about how to integrate their models and platform with existing human systems. Those who take time to think about how their high-powered methods can connect with customer experiences and front-line employee work practices are probably more likely to quickly contribute to the business’s bottom line. The best data-driven business processes are likely to be hybrid digital-people processes, not purely digital; and
• Data scientists should regularly interact with the employees and customers who they consider beneficiaries of their models, in person when possible. Such interactions can help data scientists learn about employee or customer psychology within a particular context; this knowledge can then be used to tailor data science models and systems so that they more effectively deliver business value. Our research suggests that data scientists who work in this manner are more likely to propose novel analytical solutions that cut across several channels and contribute to the bottom line more significantly.

4.4.5 Vignette V

4.4.5.1 The Myth and the Rhetoric

“Not Owning the Last Mile”

The meeting between the bank’s data science team and the “win-back” business team was not going well. The goal of the “win-back” initiative, which had brought the two teams together, was – as the name suggested – to win back customers who had stopped transacting with the bank. Nothing about the project had gone well. It had been stuck in place, making no noticeable progress, for several months. The intended purpose of this meeting had been to get the project back on track.

The heart of the problem, it seemed, was a disconnect between the data scientists – Dhara, a business analyst, and Viral, a data scientist – and the so-called liability product managers, Anish and Jalpa. Dhara and Viral were focused on how to identify customers who had the highest potential to be won back, which seemed to them a highly relevant place to start. But Anish and Jalpa kept turning the discussion to the details of how exactly a campaign to win back customers would be designed and executed, a subject that Dhara and Viral considered premature. Anish and Jalpa seemed to want the data science group to take full responsibility for implementation details, and right now, at the outset. After struggling a while longer, the participants agreed to adjourn the meeting without making any headway. In a post-meeting debrief with Dhara, Viral, the data scientist, expressed frustration: “If the data scientists and analysts do everything, why does the
bank need the product managers? Our job is to develop an analytical solution; it’s their job to execute.”

In the next meeting, though, Viral decided to change his approach. He made a determined effort to understand the concerns of product managers, and in particular why they kept insisting that the data scientists take responsibility for implementation details. This approach finally began to yield some results. As it turned out, product managers had, in the past, received numerous lists of customers to target for win-back that had come from the MIS department, but none had resulted in a successful campaign. Using such lists had been extremely challenging, partly due to difficulties in maintaining records about who had contacted which customer, and what the customer had said in that contact. The list of target customers, in the view of project managers, was a very incomplete solution to the problem, and they were tired of seeing the people who were the sources of the data behaving otherwise. For them, this exercise with the data scientists was following a familiar path to failure; their constant push-back derived from their outstanding concerns about project execution, and how failure might be rooted in the process of conceiving a campaign.

At long last, though, they achieved a fruitful meeting. Having understood the challenge from the point of view of the product managers, Viral and Dhara decided to plan an end-to-end solution with the campaign included in it. They developed a front-end application with the help of a programmer for each of the respective contact channels; telemarketers, email management teams, branch banking staff, and assets teams would feed information from their interactions with the customers into the application, which the product managers could retrieve at the end of each day. The project, after being stalled for months, finally moved ahead.

4.4.5.2 The Reality and the Lessons

This problem is related to the four others that we have identified. It is like problems 1, 2, and 3 in that it suggests that data scientists need to understand the context of the problems they are commissioned to solve. It is like problem 4 in that it also argues for data
scientists taking an interest in matters beyond the outputs of their models. But problem 5 has distinctive features that make us list it separately, the most important of which has to do with an attitude that is harbored by many data scientists, established in many early on in their educations.

Viral, and many other data scientists we interacted with during our research, considered themselves to be internal consultants in the organization that employed them. This label worked as an identity signal for data scientists, but it also suggested a distribution of labor in data science activities that placed implementation issues, or even thinking about implementation, beyond the scope of their work. They saw themselves as the proposers of solutions, not the implementers. This perspective has major drawbacks (Herring et al., 2019).

First, identifying data scientists primarily as internal consultants constrains their inclination to participate actively in revenue generation. Presuming that execution and actual revenue generation are the responsibility of business counterparts limits the likelihood that data scientists will engage in exploratory data analysis that might lead to transformative insights and important innovations. This mindset and its implicit limitation is unfortunate, because generating transformative insights and important innovations are among the most important contributions that data scientists can make in an organization.

Second, a functional separation between data science and the business often leads to a communicative void that we call, in our research, the problem of last mile. According to our informants, one of the most common reasons for the failure of data science projects is failure to execute. And one of the most common reasons for this failure is communication difficulties that arise from data scientists considering execution to be outside of their jurisdiction. When data scientists take no responsibility for execution, and business users cannot see the full relevance of the analytical insights being offered by the data scientists, failure to create business value is inevitable. Thus, our research suggests that data scientists should not only take on responsibility for execution, but also that they should pay special attention to the details of the last mile of the implementation process.
Attention paid to the site within the organization where business value is generated, typically right on the front lines, will pay dividends in assuring that data science leads to tangible business outcomes. This includes some of the issues we mentioned as a fix to problem 3, about who should use the outputs of data science models, but goes much deeper, and focuses on the point of value creation on the front lines.

The following is some specific advice that we can derive from our study, related to this problem:

- Data scientists should think of themselves as integral players in value delivery. Owning the responsibility for the last mile causes data scientists to ask questions they otherwise would not, and refine their solution concepts to improve the chance of actual value creation; and

- There is something special about the last mile in implementing any business solution. That is where business value multiplies, stutters, or fails completely. To rise to the challenge of the last mile, data scientists must think holistically about the business situation, from problem formulation to execution, and pay special attention to value creation’s end game. The idea is to conceive data science as part of a revenue-generating activity and not as an end in itself.

4.5 Concluding Remarks

Based on our research, we are arguing for a more active role for data science within organizations. Our findings suggest that compartmentalizing data science activities will fail to achieve full potential in terms of business value. We would also argue for revisiting how we train data scientists. In our view, data scientists should approach their role with an expansive mindset, wide-ranging curiosity, and a willingness to take responsibility for getting things to work outside the realm of data analysis. Both training and the framing of their roles within organizations should reflect this broader mindset. Finally, we suggest that business leaders should set the bar high for data science; they should expect from data scientists the broad-ranging contributions commensurate with their expertise, and clearly communicate their expectations to data scientists.
4.6 References


Chapter 5

5 Essay 3. Algorithmic Intelligence in Research: Prevalent Topic Modeling Practices and Implications for Academic Rigor

5.1 Abstract

Algorithms and tools originating from the field of computer science offer a great utility in enabling automated data analyses to practitioners as well as academic scholars. Researchers in the disciplines of management, organization, and information systems have increasingly started relying on such algorithms and tools. However, the increasing reliance on algorithmic intelligence has also called for caution from senior scholars in highlighting challenges for researchers, reviewers, and editors in knowledge production. Despite this caution, the information systems scholarship so far has provided limited guidance for maintaining high standards of reliability, validity, and generalizability while relying on algorithmic intelligence in research. In this study, we propose a framework to help scholars in mindfully employing algorithmic intelligence in research by alleviating identified threats to academic rigor. Our framework is based on the insights from a systematic methodological review of articles relying on topic modeling, which uncovers problematic practices prevalent in the scholarship including lack of explicit description, contentious justifications, and polarized, partial, or no validation. Our paper contributes by demonstrating how the information systems scholarship is uniquely positioned to alleviate the threats imposed by such prevalent practices.

Keywords: algorithmic intelligence, topic modeling, academic rigor, methodological review

5.2 Introduction

Recent developments in the space of big data analytics and AI have triggered fundamental changes in how researchers approach the creation, evaluation, and dissemination of knowledge. Researchers can now easily gain access to structured and unstructured data from a variety of sources, including websites, blogs, and social media pages (George et al., 2014). Such data are often perceived as too complex to be analyzed
through conventional descriptive and predictive techniques. Consequently, scholars are increasingly relying on algorithmic intelligence—characterized by new epistemic technologies and intelligent tools (Anthony 2018; Beane 2019)—in their research (Grover et al., 2020).

The increasing reliance on algorithmic intelligence brings its own challenges to knowledge production as highlighted in several editorials and commentaries from senior scholars (e.g., Abbasi et al., 2016; Johnson et al., 2019; Newell & Marabelli, 2015; Zuboff, 2015). For instance, cautioning against the uncritical embrace of big data empiricism, Johnson et al. (2019) suggest that, “[c]ompared to data generated by researchers following an intentional pre-planned research design, big data are especially at risk of a number of threats to validity” (p. 53). Additionally, Abbasi et al. (2016) warn against “black boxed” research approaches for which authors rely on sophisticated ML techniques that lack explanatory value and hence threaten the reliability of research. Consequently, it becomes hard to devise appropriate “research evaluation systems” (Gläser et al., 2010) due to the limited visibility into the micro processes of algorithmic intelligence-based methodologies.

Despite the recognition of potential methodological challenges of relying on algorithmic intelligence, we do not know enough about how these challenges manifest in academic research and how we can overcome them. Our study takes a step in this direction by asking: What are the types of prevalent practices in utilizing topic modeling—a special class of algorithms utilized in analyzing textual data—in academic research that could pose challenges for academic rigor, and what are the remedies to alleviate those challenges?

Before elaborating on how we answer the research question, we first describe algorithmic intelligence and explain our choice of topic modeling as opposed to the wide range of algorithms that could be utilized in algorithmic intelligence. Drawing on Anthony (2018) and Ratto (2012), algorithmic intelligence can be described as the use of tools and technologies that amplify the knowledge-producing capacities of humans—also referred to as epistemic technologies—by supporting and facilitating the creation,
legitimation, and critique of truth claims. Being a broad concept applicable to several classes of algorithms, with each class having an idiosyncratic script of performing the methods, an all-encompassing review will be too fragmented. Hence, to maintain consistency, we decided to review articles adopting “topic modeling,” one of the early algorithmic intelligence-based approaches that has entered the field of management and IS (Hannigan et al., 2019). There have been several attempts, by established scholars, to make the method more accessible within academia through reviews and developmental workshops (e.g., Hannigan et al., 2019; Schmiedel et al., 2019), which have fueled the already high interest in the method among scholars and afforded a decent sample for us to conduct a systematic review, as described next.

We answer the research question by proposing a framework based on a systematic methodological review of articles applying topic modeling in top journals of management, organizations, and IS. First, we uncover prevalent practices and patterns of justifications in studies that relied on topic modeling, thereby critically reflecting on practices that are problematic from the perspective of academic rigor. Our review identifies three abstract themes signifying prevalent, but rather problematic practices, including lack of explicit description, contentious justifications, and polarized, partial, or no validation. Second, for each of the themes identified, we discuss implications for reliability, validity, and generalizability. Finally, we propose a framework that can be used by authors, reviewers, and editors as a frame of reference to mindfully ascertain that their algorithm-driven methods comply with key academic values. Our paper contributes to the emerging interdisciplinary scholarship on algorithmic intelligence at the intersection of management, organization, and IS disciplines. We demonstrate how IS scholarship can bear the flag of promoting rigorous research across the business disciplines in responsibly adopting algorithmic intelligence in academic research (Saar-Tsechansky, 2015; Tarafdar & Davison, 2018).

5.3 Systematic Methodological Review

Topic modeling is a popular ML technique that helps to identify latent themes in a collection of text-based documents. It can be considered a representative example of a
class of algorithms utilized in research for analyzing textual data. Due to early adoption and popularity of the method among scholars, we could collect a decent sample of articles to conduct our systematic review.

We collected articles published in top journals in the disciplines of management, organization, and IS (see Table 5.1). Our primary search focused on articles that contain any variation of the phrase “topic modeling” anywhere in the text. Additionally, we also searched for the phrases “latent dirichlet,” “latent semantic,” and variations of the phrase “matrix factorization” to capture articles that apply similar algorithms to identify latent semantic concepts that can be used to describe texts (e.g., Evangelopoulos et al., 2012; Heldens et al., 2020). We included articles published before December 31, 2019 that referred to these keywords, but excluded those that 1) refer to topic modeling algorithms as examples or alternative but do not apply them; 2) cite topic modeling only for the purpose of referencing; 3) apply the specific algorithm(s) but not with the goal of capturing the semantic concepts or dimensions that represent the content of texts; and 4) consider topic modeling, but are not empirical in nature (e.g., methods or review papers). Applying these selection criteria resulted in a pool of 40 articles in the final sample from the original list of 101. Table 5.2 (first two columns) lists the articles in our sample.

Our findings emerged through an iterative process of exploratory coding and systematic analysis. To start with, both authors open coded different subsets of articles—21 in total—across three typical phases of research, including research design, data collection, and data analysis, to gain a better understanding of the methodological steps involved when applying topic modeling and examine how academic rigor manifests

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20 We utilized the EBSCO host databases and search tool, because it allows us to search for certain keywords in the full text of the paper (as opposed to e.g., only in the title or abstract). Some errors might exist (Evangelopoulos 2016), but we mitigated this concern by utilizing multiple keywords.

21 These algorithms differ from traditional clustering algorithms such as K-means based on the output. Those algorithms that we classify as “topic modeling” algorithms result in two matrixes as output: one that assigns terms to latent semantic concepts (topics), and one that assigns latent semantic concepts to documents.

22 For example, we did not include articles in which these techniques are primarily used for dimensionality reduction, without intending to capture the semantic meaning of a textual corpus.
across research stages (Dubé & Paré, 2003). We identified data preparation as an important yet previously overlooked subphase during data collection that is not as salient in the traditional forms of research (Shadish et al., 2002), but critical when applying algorithmic intelligence. In addition, we realized the need to code final model validation as a distinct phase from data analysis, as it involves several additional activities that go beyond the core data analysis. Based on our initial exploration, we constructed a more detailed coding scheme to aid us in the systematic analysis of articles. For each article, we recorded whether the researchers reported on the different steps performed in each of the phases of research design: data collection and preparation, data analysis, and final model validation. In addition, we captured their justifications as to why these specific steps were undertaken by them and how they validated choices. This allowed us to identify common practices, which we could assess in correspondence to academic rigor. See Table C1.1 (Appendix C1) for our detailed coding scheme along with sample questions and illustrative examples.23 As a final step, we abstracted higher order themes based on consistent and repetitive practices across phases, which we present next.

5.4 Prevalent Research Practices and Implications for Academic Rigor

We identified three higher order themes that are consistent and repetitive across phases: lack of explicit description, contentious justifications, and polarized, partial, or no validation24. For each, we first discuss the prevalent problematic practices that we observed, followed by their implications for reliability, validity, and generalizability. The findings are summarized under the last four columns (Criteria 1 to 4) in Table 5.2.

23Systematic coding is done by both authors of this paper. First, both authors coded the same five papers to test the usability of the coding framework and its definitions. We compared our codes and settled on the differences after discussions and subsequently divided the remaining papers. We met on a regular basis to discuss insights and decided to include relevant quotes in our shared coding table such that we could evaluate and revise each other’s decisions and codes.

24As an intermittent stage, we first organized our findings for each research phase distinctly and then abstracted the higher order themes. We have only reported those higher order themes here. The detailed phase-wise findings are available on request.
5.4.1 Lack of Explicit Description

5.4.1.1 Prevalent Research Practices

Researchers need to make a series of choices when applying algorithmic intelligence (see Appendix C2 for a brief note on the nature of choices to be made in applying topic modeling in each of the research phases). Availability of (competing) alternatives makes it imperative for researchers to explain the choices they make in their studies. Yet, one of the most salient themes in our findings is the lack of explicit description regarding what choices authors make, as well as how and why they arrive at such choices.

In the research design phase, several articles in our sample do not explain why they adopt automated text analysis (of which topic modeling is a subcategory) or how relying on algorithmic intelligence is better than alternative methods (e.g., Moody & Galletta, 2015). Similarly, while most articles in our sample relied on unsupervised topic modeling approaches, very few of them explicitly consider the strengths and weaknesses of such approaches or explain why they opted for the fully unsupervised approach (e.g., Bogusz & Morisse, 2018). This lack of description makes it hard to evaluate the chosen design and impossible to reason if an alternative approach could have been more suitable in the given context.

Our review suggests that information regarding all the different ways in which data have been pre-processed is generally not available either. In many cases—as most data pre-processing steps are optional—readers are left wondering whether the researchers did not perform the steps, or whether they did not report on them\(^\text{25}\) (e.g., Giorgi & Weber, 2015). A handful of researchers explicitly mention not performing certain data preprocessing steps to avoid (human) bias (e.g., Lee et al., 2016; Shi et al., 2017).

Though, researchers will always need to do some preprocessing (at least dealing with non-alphabetic characters).

The lack of explicit description is a consistent theme in the case of data analysis as

\(^{25}\)With the exception of Shi et al. (2016) who explicitly argue that pre-processing is hardly needed in their case.
well. While all papers in our sample mention which algorithm was adopted to discover the semantic structure of texts, the papers are hardly explicit about the parameter settings (e.g., number of topics, hyperparameters, iterations). Algorithmic model outputs can be very sensitive to parameter configurations, yet some articles do not mention any parameters at all (e.g., Huang et al., 2019). While most papers do mention the number of topics or dimensions, this chosen value is often not explicitly justified. Other parameters such as the hyperparameters (e.g., in the case of Latent Dirichlet Allocation—LDA), number of iterations, convergence measure, and learning method, are often overlooked (e.g., Choudhury et al., 2019; Tuertscher et al., 2014).

Strikingly, none of the papers report on how they dealt with the randomness that is embedded in most topic modeling algorithms. Most, if not all, ML algorithms have inherent randomness in the initialization and training processes. Accordingly, it is a well-recognized challenge that multiple runs of the same topic model on the same training data with the exact same parameter settings could result in different outcomes (Belford et al., 2018). A quick-fix to overcoming this challenge is to set a “random seed” to facilitate results-reproducibility (Aguinis et al., 2018). Still, working with random seeds involves several choices to be made by the researchers. For instance, researchers may arbitrarily pick one random seed and continue their experiments and analysis while keeping the random seed the same; they may perform sensitivity analyses with different random seeds after completing the analysis, or they may experiment with different random seeds and choose the “best” model based on certain evaluation criteria during data analysis. In practice, we found very little information pointing to how researchers deal with randomness in algorithmic intelligence-enabled approaches.

It is noteworthy that explicit description is a continuum (Aguinis et al., 2018). Most of the papers in our sample are explicit about some choices, but not about other choices or about the rationale behind those choices. There are some examples of papers that are highly transparent (e.g., Chen et al., 2019a; Gong et al., 2018), but only very few. These

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26Interestingly, evidence suggests that the most stable models are not always the “best” models in the sense that “the topics are semantically coherent and provide a useful insight into the content of the corpus” (Belford et al., 2018, pp. 5).
patterns are summarized under Criteria 1 and 2 in Table 5.2.

5.4.1.2 Implications for Academic Rigor

The observed lack of explicit description obviously threatens transparency and eventually replicability as well, which are two integral dimensions of reliability (Aguinis & Solarino, 2019; Gibbert et al., 2008). It is impossible to replicate results produced by algorithmic intelligence if other researchers have no visibility of the choices that have been made across research phases. Even if the results could not exactly be reproduced, researchers should still provide enough information about the process that led them to choose certain model configurations over others. This has cascading implications for generalizability as well. Even if generalizability is not an intended objective of a particular study, the paper should still include enough information about the decisions made to allow other stakeholders to assess the applicability and relevance of the findings to other contexts (Eisenhardt, 1989; Gibbert et al., 2008; Yin, 1981). However, we find that many studies in our sample fail to facilitate such “analytical generalizability” (Gibbert et al., 2008) due to lack of transparency.

The lack of explicit description generally prevents other researchers, reviewers, and editors from evaluating whether the choices made were applicable given the specific research context. All steps across research phases are likely to have been performed based on several assumptions. Without knowledge of these steps and the underlying assumptions, fellow scholars have no way of independently validating the quality of the knowledge being created. Lack of a “clear chain of evidence” thus raises questions around the validity of findings (Bagozzi et al. 1991; Yin, 1994).

5.4.2 Contentious Justifications

5.4.2.1 Prevalent Research Practices

Explicit description is not enough; researchers need to provide valid justifications for their choices. In this theme, we document that even when articles are explicit about—and justify—their choices, these justifications are frequently found to be either contentious or partial at best.
Following Best Practices. One of the most common classes of justification for choices made while applying topic modeling in management and IS research can be represented as following best practices, where authors follow other scholars’ suggestions and leads without much pondering about contextual relevance of the tools being adopted. For instance, while making research design choices, Croidieu and Kim (2018) rely on a topic modeling approach because other studies have applied methods relying on word co-occurrence “in similar theoretical situations” (p. 9). Similarly, Huang et al. (2019) reason for applying automatic content analysis methods to respond to “calls to adopt text mining methods to study online user-generated content” (p. 397). In fact, most of the papers in our sample choose LDA as the model to perform topic modeling and the most common reason for this choice seems to be, ironically, the popularity of the algorithm. Typically, studies introduce LDA by highlighting that it is a widely used (Dong et al., 2018; Hu et al., 2019; Huang et al., 2018), if not the most popular topic modeling algorithm (Geva et al., 2019; Gong et al., 2018; Huang et al., 2019; Shi et al., 2016; Singh et al., 2014).

Articles also tend to follow best practices in data collection and preparation. Kaplan and Vakili (2015) followed “typical practice” by removing stop words such as “the,” “and,” “that,” or “were” (p. 1443). Similarly, Gong et al. (2018) follow a “standard procedure” by removing annotations, tokenizing sentences, and removing stop words using a “standard” dictionary (p. 813). Giorgi et al. (2019) on the other hand followed a “standard procedure” of removing rare words and performing stemming (p. 824). Many of these papers refer to studies by Aral et al. (2011) and Croidieu and Kim (2018) as the main references for applying these practices. Interestingly, even though all these studies follow “standard procedures,” we do clearly observe differences between alleged standards and hence these might not universally apply in all contexts.

In the data analysis phase, several articles choose values for parameters such as the number of topics and hyperparameters by following best practices. For instance, Haans (2019) cites Kaplan and Vakili (2015)—both articles in our sample—and follows their precedence in setting the value of 100 as the “typical number” of topics for their study. In setting hyperparameters, Li et al. (2016) and Huang et al. (2018) follow recommendations by Blei et al. (2003) and Steyvers and Griffiths (2006), respectively, in
choosing specific, fixed values. Overall, the institutionalization of these best practices overshadows the need for evaluating the relevance and applicability of these tools and approaches in the given context, rendering such justifications contentious.

**Object-Justification Mismatch.** We term object-justification mismatch as a practice where the researchers resort to justifying the choice of one object as the default and implicit justification for corresponding choices of other objects. For instance, articles in our sample often conflate the reasons for relying on algorithmic intelligence, for choosing an unsupervised approach, for adopting a topic modeling approach, and for choosing LDA, by providing only one justification: that it allows for making sense of diverse, unstructured, large amounts of data. While this explanation could be a valid justification for relying on algorithmic intelligence, its suitability for applying topic modeling or choosing a specific algorithm is debatable as there are several automated alternatives for topic modeling (e.g., dictionary-based approaches or clustering techniques). Similarly, many articles in our sample treat unsupervised text mining, topic modeling, and LDA as synonymous by highlighting the algorithm’s inductive nature and its capability to capture polysemy (Croidieu & Kim, 2018; Giorgi et al., 2019). Arguably, these characteristics also apply to other unsupervised algorithms such as Latent Semantic Analysis (LSA), Non-Negative Matrix Factorization (NMF), and Structural Topic Models (STM). This practice of black-boxing multiple choices into one by ignoring the hierarchy of decisions renders the justification as contentious.

Like in the case of explicit description, for this theme there are also exceptions where articles do provide thorough and valid justifications for their choices (e.g., Bao and Datta, 2014; Nielsen & Börjeson, 2019; among others). Yet these examples are very few (see Criterion 3 under Table 5.2 for details). It is noteworthy that the transparency criteria (criteria 1 and 2) in Table 5.2 have a cascading effect on the justification criterion (Criterion 3). For instance, Haans (2019) would appear to be thorough in justifications, because most reported choices are justified, but the article scores medium rating in terms of transparency, which means it does not justify all the important choices it could and should have. Hence, the net justification score for Haans (2019) (with medium transparency) would be lower than, say, Bao and Datta (2014) (with high transparency)
even though at the face value, the score for justifications shows thorough for both.

### 5.4.2.2 Implications for Academic Rigor

To ensure the validity of their findings, researchers need to both provide “logical reasoning that is powerful and compelling enough to defend the research conclusions” and guarantee that the “study investigates what it claims to investigate” (Gibbert et al., 2008, p. 1446). The methodology and its outputs should render an accurate observation of reality (Denzin & Lincoln, 1994), and thus choosing the right method appropriate for the given context is of paramount importance. Our findings suggest, however, that researchers might be overlooking the applicability of their approach when simply following best practices and failing to acknowledge the hierarchy of decisions through object-justification mismatch. For instance, while certain preprocessing steps make sense for some texts (e.g., removing pronouns and performing stemming on relatively simple texts with little ambiguous meaning), other texts may require more tailored approaches (e.g., removal of industry-specific stop words or lemmatizing nouns and verbs). Similarly, there are various scenarios where topic modeling might be an appropriate choice, but LDA may not be—but if the choice for LDA is made as a default without considering more applicable approaches, these challenges remain unnoticed.

Following best practices in particular also threaten the academic rigor in IS discipline at a higher level. First, there is a risk of amplified limitations when articles simply follow best practices but do not reflect on the challenges associated with these practices. This lack of acknowledging the limitations of best practices is problematic for building and disseminating knowledge in the field. Second, we identified that best practice implementations actually differed in practice. For example, “standard approaches” to preprocess the data differed among articles in our sample. This is troubling, because it suggests that researchers have not yet reached consensus on

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27For example, STM might be a better choice if the authors wish to do some correlation analysis based on metadata, while LSA and NMF have the benefit of allowing for TFIDF weighting (O’Callaghan et al., 2015). NMF might also work better on short texts (Chen et al. 2019b).
supposed best practices. Finally, the best practices have self-reinforcing nature. By labeling a certain practice as a best practice, the author(s) contribute to institutionalizing the particular practice as a best practice through their research article. Subsequent articles then cite the earlier article claiming it to be the best practice and the cycle goes on. This self-reinforcing cycle in turn overshadows the rationale behind adopting a particular practice.

5.4.3 Polarized, Partial, or No Validation

5.4.3.1 Prevalent Research Practices

While intermediate validation happens when authors provide empirically-based justifications for making specific choices during data preparation and analysis, final model validation is focused on evaluating the overall model and outcomes. Both types of validation are important to tackle the black-boxing nature of ML tools (Müller et al. 2016). We observed three broad themes regarding if and how researchers validate their topic models.

*Dualism in Intermediate Validation.* During the data preparation and analysis phases, most articles in our sample would empirically validate their choices *either* by relying on computational measures and aiming for objectivity *or* by relying on qualitative measures and aiming for contextual interpretability, but rarely both. In other words, while we have progressed from *dualism* to *duality* in examining technology through research (Orlikowski, 1992), we are still wrestling with *dualism* in adopting technology in research. For instance, on the one hand, several articles in our sample calculate the *perplexity scores* of models with different numbers of topics and choose the number of topics that provided the lowest or optimal perplexity toward aiming for objectivity (Dong et al., 2018; Nielsen & Börjeson, 2019; Samtani et al., 2017). Other commonly adopted measures include log-likelihood estimations (e.g., Bapna et al., 2019; Croidieu & Kim, 2018) and topic divergence measures (e.g. Geva et al., 2019). On the other hand,

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28Perplexity can be described as “the predicted number of equally likely words for a word position on average”, and is used to determine the predictive performance of a given model (Bao & Datta, 2014, p. 1379).

some articles provide more qualitative, contextual reasons for choosing parameter values. These articles generally refer to Chang et al. (2009), who argue that computational measures such as perplexity and held-out likelihood “are useful for evaluating the predictive model, but do not address the more exploratory goals of topic modeling” and even conclude that “models which achieve better predictive perplexity often have less interpretable latent spaces” (pp. 1). For instance, Singh et al. (2014) qualitatively compared the topic outcomes of LDA models with different numbers of topics, and concluded that their chosen model “leads to qualitatively similar results” (p. 42). Similarly, Giorgi and Weber (2015) consider both measures of word intrusion and topic interpretability to arrive at their topic specifications. Larsen and Bong (2016) experimented with different numbers of topics and evaluated these models by determining the false negatives, true positives, and false positives in the given context. They conclude that increasing the number of topics “yielded only insignificant improvements along with longer convergence time” (p. A2).

Overall, we observed a dualism in adopting either qualitative or quantitative techniques in intermediate validation. Only a handful of papers combine computational measures with qualitative evaluation to determine appropriate model parameters. Among those are Kaplan and Vakili (2015), who limit the topics to a number that “provides both statistically and semantically meaningful topics” (p. 1442), while also relying on expert assessment to find a meaningful threshold for assigning topics to documents; and Bao and Datta (2014), who check perplexity scores of different models, and also examine semantic coherence of topics based on human input to discover “substantively interesting information” (p. 1385). Apart from these exceptions, most of the articles reside at polar ends of the quantitative versus qualitative divide.

**Lack of Final Model Validation.** Surprisingly, several articles in our sample do not report any validation tests on the final topic model (e.g., Choudhury et al., 2019; Xu et al., 2014). Several of the articles that fail to report any validation results for their final topic models do end up using the topic model output as independent or control variables in follow-up analyses. For instance, Hu et al. (2019) apply topic modeling to derive a set of features from texts, which constitute independent variables in another ML model that
predicts brand personality. These authors do validate their overall model that predicts brand personality; however, they end up black-boxing the topic model by not reporting any validation for this step. Similarly, Love and Hirscheim (2016), Gunarathne et al. (2018), and Xu et al. (2014) hardly validate their models based on LSA. Despite performing LSA only as a preliminary step in their analysis, this step arguably still needs to be validated as any inaccuracies propagate into the final results. Note that in Table 5.2 (Criterion #4), our findings only reflect the validation patterns of topic models, as opposed to other, complementary steps in the analysis.

**Partial Final Model Validation.** While applying topic modeling, scholars could potentially validate their final topic models by evaluating the semantic quality of topic models, by performing sensitivity analysis, by comparing with other methods, and by comparing with external information.

Validating the semantic quality of topic models is one of the most common approaches followed by researchers, which can be done by ascertaining quality of topics (more common) and by examining topic-document allocation (less common). Scholars typically ascertain the quality of topics by qualitatively examining the top 10-30 words to see if the dimensions make sense and assign a label to them. For instance, Kaplan and Vakili (2015) follow this labeling approach to validate the usefulness of topics in identifying separate ideas with the help of human experts. Several other examples of humans labeling the topic model output can be found in our sample (e.g., Bapna et al., 2019; Gong et al., 2018; Haans, 2019; Shi et al., 2016). A few papers in our sample also perform computational checks to validate the quality of the topics (e.g., Yue et al., 2019).

A much less common approach to validate the semantic quality of topic models involves examining the topic-document allocation. For instance, Bao and Datta (2014) argue that it is important to test whether the topic assignments make sense and validate the meaning of the topics against sample texts to demonstrate that they corroborate well with the underlying documents. Researchers may also ask human experts to agree or disagree with the topics generated by their topic models, to see if topic model output aligns with human sense-making (e.g., Samtani et al., 2017).

Another validation approach includes establishing the sensitivity of the topic model
output to choices made during data collection and analysis. First, a common approach is to examine sensitivity to different parameter values. As with intermediate validation, the number of topics is again the most common parameter being considered for sensitivity analysis (e.g., Haans, 2019; Shi et al., 2016; Yue et al., 2019). Second, some authors perform sensitivity analysis by using left out samples or different data sources (e.g., Geva et al., 2019; Gong et al., 2018). Third, researchers may consider evaluating the sensitivity and stability of the topic model to different runs with different random seeds, although very few articles acknowledge this challenge (e.g., Croidieu & Kim, 2018). Finally, a few studies reconsider their choice of algorithm and compare their model output against that of other topic modeling algorithms, for instance by comparing LDA with LSA (e.g., Bao & Datta, 2014; Larsen & Bong, 2016).

Yet another class of approaches for validation includes empirical comparison with a range of other methods and measures, though only a few studies in our sample adopt this approach. First, some authors rely on computational measures to compare topic model outputs with other text mining methods. For instance, Bao and Datta (2014) compare their topic model output with categorical K-nearest neighbors method using t-tests. Nielsen and Börjeson (2019) compare their topic model outcomes with a technique for science mapping, i.e., co-word mapping, and consider the overlap between the two methods. Second, some authors empirically compare their topic model outputs with other, non-text mining approaches. For instance, Shi et al. (2016) compare the business proximity measure developed using topic modeling with a simple category-based industry classification and then perform a simple statistical comparison of the two. Similarly, Croidieu and Kim (2018) compare their topic model outcome with adoption density, an established approach of measuring legitimacy in literature.

Finally, the least common validation approach is to compare topic model output with external information. The underlying logic is that if the topics are valid, they should covary with some external information. For instance, Bao and Datta (2014) examine if the number of risk factors around the topic of macroeconomics risks inferred from their topic model show increase during the period of global financial crisis. They conclude that their topics are valid because they double around the year 2009. Similarly, few other
papers (e.g., Huang et al., 2018; Samatani et al., 2017; Shi et al., 2016) compare their topics with industry wide events.

Like the other two themes, it is noteworthy that in our sample, we also find some good examples of final model validation (see Criterion #4 in Table 5.2). In total however, we identified only four papers (Bao & Datta, 2014; Huang et al., 2018; Shi et al., 2016; Sidorova et al., 2008) that perform extensive validation in the sense that they evaluate the semantic quality of the topic model, perform sensitivity analyses or compare with other methods, and compare topic model output with external information.

5.4.3.2 Implications for Academic Rigor

Naturally, the prevalent practices of validation pose serious threats to the academic values of validity and generalizability. Validating the intermittent and final model plays an important role in establishing the internal and construct validity of research. For instance, failing to establish the semantic quality of topics by checking the topic vectors and going back to original documents to check topic-document allocations makes it difficult to establish whether the authors are actually measuring what they intend to. Similarly, without performing sensitivity analysis of the chosen parameters, it is hard to establish whether the results happened by chance or were actually valid in the given empirical context. All data processing steps and parameter configurations potentially impact the results. Especially in the cases where model output subsequently becomes input for statistical modeling, validating through sensitivity analysis is extremely important, as it helps determine whether, indeed, “significant” results were the outcome of real-world phenomena or merely the product of modeling choices.

Performing sensitivity analyses might also help researchers to evaluate the extent to which their findings are generalizable. One promising approach adopted by some of the studies in our sample (e.g., Geva et al., 2019; Gong et al., 2018) is to perform a sensitivity analysis on different data, e.g., data collected at different times or from different platforms. Doing so allows researchers to assess specific model outputs and results in comparison with their specific research configurations and whether they can be transferred to other contexts. In fact, validation techniques to establish generalizability are extremely important due to inherent limitations of algorithmic intelligence. As Li et
al. (2016) argue, “LDA lacks robust external validation methods for evaluating its results, so most studies evaluate their LDA models using internal validation” (p. 1068). One way to compensate for this limitation is to compare model output with other methods and external information in order to explore similarities, differences, and complementary insights across research contexts.

Arguably, to ensure the reliability, validity, and generalizability of research findings, researchers relying on algorithmic intelligence should consider the internal quality and “meaning” of the model output, perform sensitivity analyses and consider alternative methods, and compare their model output with external information.

In addition to the types of validation techniques discussed so far, the nature of validation techniques is equally important (which could be quantitative or qualitative as narrated in the subsection on dualism in intermediate validation). Whereas some researchers are convinced that algorithms are more objective and that quantitative measures are more unbiased (e.g., Indulska et al., 2012), others argue that this is not always the case and are more inclined to focus on the semantic meaning of the model output. These observations correspond to an ongoing debate that questions the objectivity of algorithms in both research and practice, and urges for the inclusion of qualitative domain knowledge in the process of training and validating algorithms (e.g., Abbasi et al., 2016; Johnson et al., 2019; Newell & Marabelli, 2015; Zuboff, 2015). It seems that algorithmic intelligence transcends the boundaries between quantitative and qualitative realms and that, ideally, researchers need to combine qualitative and quantitative validation techniques.

5.5 Proposed Framework

We introduce a framework to assist researchers, reviewers, and editors in the process of knowledge production while engaging with topic modeling in particular, and algorithmic intelligence in general, in management and IS research. Our framework (Figure 5.1) has three main pillars: achieving transparency, customizing for context, and combining quantitative and qualitative tools for continuous validation. It is geared toward invoking mindful engagement with algorithmic tools for researchers to (upfront) think and be transparent about the choices and justifications involved, and validate those justifications.
We have kept the framework intentionally open to ensure that it does not turn into yet another best practice.

5.5.1 Achieving Transparency

One of the most evident, yet most important, recommendations is the need for transparency in research based on algorithmic intelligence. To mitigate concerns related to the black-boxing nature of algorithms and ensure the reliability, validity, and generalizability of their findings, researchers need to be transparent about and explicitly reflect on what choices they make.

First, our framework compels researchers to explicitly consider and report on what decisions have led to the final model. In particular the framework guides researchers to think about the relevant class of algorithms and the specific algorithm that they have chosen to rely on in their research design; the specific steps that have been performed to prepare the data for analysis; the tools that have been adopted to perform the analysis and the configurations of input parameters that have led to the final model, and the variety of quantitative and qualitative measures that have been used to validate the (intermediate) results. Second, the framework helps researchers to critically reflect on and also report on who has been involved in making these decisions, and what assumptions are underlying these decisions. In particular, researchers are encouraged to unpack the assumptions underlying the specific algorithms and tools, as well as reflect on their own assumption based on which they have decided to perform certain preprocessing steps or pick a certain configuration of parameter settings. For instance, the LDA algorithm “is based on the bag-of-words assumption, which states that the order of words in a document does not matter” (Bao & Datta, 2014, p. 1376). Hence, researchers adopting LDA need to unpack this assumption in order to be able to assess whether it applies to their context, as discussed next.

5.5.2 Customizing for Context

While achieving transparency is concerned with being explicit about and reporting on the decisions made, customizing for content is about assessing the extent to which the underlying assumptions fit with the specific research context and whether the chosen
approach actually outperforms alternative approaches. Within the scholarly discourse, it is well accepted that researchers should design their methodological approach in line with the context and research question, and that all phases of research should be in sync with each other. Our framework recommends customizing the practices for each study, rather than following the so-called best practices or black-boxing the hierarchy of choices. In this process of customization, authors are encouraged to explore the full repertoire of competing tools available at their disposal, or potentially even build novel tools more suitable to the given context.

Our framework triggers mindful considerations for customizing algorithmic tools to the specific research context. For example, researchers are triggered to think afresh whether they need to rely on algorithmic intelligence in the first place, and if so, which classes of algorithms they can choose from. For instance, if the data are text from annual shareholder letters, but the sample size is too small, it might be better to employ qualitative coding by human experts, rather than employing an algorithmic intelligence-based approach. Similarly, researchers are triggered to critically reflect on and explain why the underlying assumptions of the adopted approach (which have previously been unpacked) align well with the research objectives and the nature of data. If the data are very noisy yet context-specific, researchers may consider existing enriching “standard” lists of stop words and remove other non-meaningful context-specific words too.

5.5.3 Combining Quantitative and Qualitative Tools for Continuous Validation

Use of algorithmic intelligence mandates that researchers iteratively validate decisions at each research stage and also validate the final model. Our framework compels researchers to actively explore the different types of both quantitative and qualitative validation tools while applying algorithmic intelligence, and to critically reflect on the applicability of such methods to their specific research context. First, our framework pushes researchers to be mindful about the need for continuous validation, not just at the final stages of the research. For instance, researchers are encouraged to, from the start, think about the potential consequences of their choices at each stage of research, and empirically validate if the consequences are in line with the expected outcomes based on
the justifications provided. Second, our framework pushes researchers, reviewers, and editors to consider model performance from both quantitative and qualitative perspectives, in an attempt to maintain rigorous standards while still paying attention to the meaning and contextual relevance of these models. Finally, researchers are encouraged to also explore ways to assess the external validity of the research.

Overall, our framework recommends that the three pillars need to go hand-in-hand: Customizing for context is about tailoring tools and techniques to the specific research context and justifying choices based on theoretical rationale, while continuous validation is about evaluating those choices based on empirical rationale. In other words, these two pillars are two sides of the same coin. Together, when backed by the third pillar, transparent description of choices and assumptions, the dimensions of the framework make a research project rigorous and of high academic standards.

5.6 Limitations

Our study is not without its limitations. We acknowledge that academic articles are the outcome of the editorial review process and that authors are constrained by space availability in the academic publications. We also acknowledge that the space allocated for describing topic modeling is likely to vary in accordance to the role of topic modeling as a primary method or a secondary method in a particular study. Because of these reasons, what we infer from the published papers might not be a true representation of what the authors might have actually done in their studies. For instance, it is possible that authors might have extensively validated their topic models in their study, but they chose not to report these validation steps in the published version of the paper due to space constraints. Our critique is not intended to pin-point particular articles or scholars, but is instead a self-reflection on our community as a whole. We, the authors of this manuscript, have also in past engaged with some of the problematic practices we highlight and hence are equally responsible for the state of our discipline. It is our hope that this manuscript guides us in doing better.

5.7 Concluding Remarks

The increasing reliance on algorithmic intelligence has been characterized by experts as
an inflection point for research in social sciences (Athey, 2019). Amid such exciting times, what we do today is likely to have lasting consequences in the future iterations of social science research, and the IS discipline is “uniquely positioned” to “claim [the] territory” in this space (Goes, 2014, p. viii). It also means that it is the responsibility of the IS discipline to bear the flag and guide other social science disciplines in carefully applying algorithmic intelligence in academic research while maintaining the highest standards of academic rigor. The framework we propose, based on a rigorous methodological review, is a step in that direction in uniting and guiding the disciplines of social science through IS scholarship.

5.8 References


42(3), 805-829.


Quartely, 39(4), III–VI.


Table 5.1: List of Journals

<table>
<thead>
<tr>
<th>Title (Abbreviation)</th>
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<tbody>
<tr>
<td>Administrative Science Quarterly (ASQ)</td>
<td>Journal of Management Studies (JMS)</td>
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<tr>
<td>Information and Management (I&amp;M)</td>
<td>Journal of the Asso. for Information Systems (JAIS)</td>
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<tr>
<td>Information and Organization (I&amp;O)</td>
<td>Management Science (MgmtSci)</td>
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<tr>
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<td>MIS Quarterly (MISQ)</td>
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<tr>
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<td>Organization Science (OrgSci)</td>
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<tr>
<td>Journal of Information Technology (JIT)</td>
<td>Organization Studies (OrgStd)</td>
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<tr>
<td>Journal of International Business Studies (JIBS)</td>
<td>Research Policy (RP)</td>
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<td>Strategic Management Journal (SMJ)</td>
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Table 5.2: List of Articles by Journal and Summary of Findings per Paper

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<tr>
<th>Authors, Year and Title</th>
<th>Journal</th>
<th>Criteria²⁹</th>
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</table>

²⁹After doing extensive coding, we decided to summarize the findings for each paper according to four criteria. **Criterion 1**: Transparency of Choices (Low, Medium, High); **Criterion 2**: Transparency of Justification (Low, Medium, High), **Criterion 3** = Nature of Justifications (Not Applicable, Partial or Thorough), **Criterion 4**: Nature of Validation (Hardly, Partial, Extensive). More details in Online Appendix C3.
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<th>Authors</th>
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<td>Gong J, Vibhanshu A, Li B</td>
<td>Examining the Impact of Keyword Ambiguity on Search Advertising Performance: A Topic Model Approach</td>
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<td>Larsen KR, Bong CH</td>
<td>A Tool for Addressing Construct Identity in Literature Reviews and Meta-analyses</td>
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<td>Shi Z, Lee GM, Whinston AB</td>
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<td>Sidorova A, Evangelopoulos N, Valacich JS, Ramakrishnan T</td>
<td>Uncovering the Intellectual Core of the Information Systems Discipline</td>
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<td>See No Evil, Hear No Evil? Dissecting the Impact of Online Hacker Forums</td>
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<td>Giorgi S, Weber K</td>
<td>Marks of Distinction: Framing and audience appreciation in the context of investment advice</td>
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<td>Haans RFJ</td>
<td>What's the value of being different when everyone is? The effects of distinctiveness on performance in homogeneous versus heterogeneous categories</td>
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<td>Kaplan S, Vakili K</td>
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<td>Lash MT, Zhao K</td>
<td>Early Predictions of Movie Success: The Who, What, and When of Profitability</td>
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<td>Lee GM, Qiu L, Whinston AB</td>
<td>A Friend Like Me: Modeling Network Formation in a Location-Based Social Network</td>
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<td>Li W, Chen H, Nunamaker JF</td>
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<td>Samtani S, Chinn R, Chen H, Nunamaker JF</td>
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<td>Antons D, Joshi AM, Salge TO</td>
<td>Content, Contribution, and Knowledge Consumption: Uncovering Hidden</td>
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<td>Chen L, Baird A, Straub DW</td>
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<td>Gefen, D., Larsen, K.R.</td>
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<td>Xu J, Chau M, Tan BCY</td>
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<td>Choudhury P, Wang D, Carlson NA, Khanna T</td>
<td>Machine learning approaches to facial and text analysis: Discovering CEO oral communication styles</td>
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<td>Indulska M, Hovorka DS, Recker J</td>
<td>Quantitative approaches to content analysis: identifying conceptual drift across publication outlets</td>
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Figure 5.1: Framework for Applying Algorithmic Intelligence in Academic Research
5.10 Appendices

5.10.1 Appendix C1: Coding Scheme

After several iterations of open coding between the authors and extensive reading of secondary literature on topic modeling, we developed a coding scheme to uncover the prevalent practices adopted by scholars in applying topic modeling, as exhaustively as we can. Our coding scheme also reflects the nature of choices the scholars are required to make when utilizing topic modeling in their research, as described in the next Appendix (C2). An abstracted version of our coding scheme is represented in Table C1.1. The detailed coding scheme, involving the full range of available tools and choices that have to be made when applying topic modeling, is not included here but available on request.

5.10.2 Appendix C2: Description of Choices in Topic Modeling

Considering the complexities involved in analyzing textual data, it is important to understand the nature of choices that researchers need to make during each phase of research while adopting topic modeling. This appendix should help those readers who are less familiar with topic modeling in making sense of the context of choices being made in topic modeling-based research.

5.10.2.1 Research Design

Depending on their research questions and research goals, researchers may differently design their data collection and analysis approaches. When it comes to utilizing algorithmic intelligence, researchers may do this along with inductive, deductive, as well as abductive research designs. In our sample, most of the articles use algorithmic intelligence to achieve one of three research objectives: designing and testing a methodology, developing a system or framework, or developing a new measure and testing theory.

Applying algorithmic intelligence in research involves a hierarchy of decisions at the research design stage. To start with, relying on algorithmic intelligence to achieve a given research objective itself is a conscious choice the researchers need to make. After
having made the decision to rely on algorithmic intelligence, researchers still need to choose from different classes of algorithms. This includes, for example, the choice of whether to adopt supervised or unsupervised learning approaches, and whether to apply topic modeling or other (text-mining) algorithms. After choosing to rely on topic modeling to analyze textual data, the choice of algorithm still remains. Different algorithms exist that may be classified as topic modeling algorithms because they result in similar output: This class of algorithms includes, for example, Latent Semantic Analysis (LSA), Nonnegative Matrix Factorization (NMF), Latent Dirichlet Allocation (LDA), and Structural Topic Modeling (STM), as well as variations such as Probabilistic LSA (PLSA), supervised and hierarchical LDA, and LDA2Vec.

5.10.2.2 Data Collection and Preparation

Acknowledging that data collection is an integral part of any methodology, we coded articles on the nature of the data, the general approach for collecting the data, and the sampling criteria used in the process of data collection. We limited our coding in this phase to capturing the chosen approach and the level of transparency in reporting each of the elements.

Barring a few exceptions (e.g., Gong et al., 2018; Singh et al., 2014), most of the papers in our sample use publicly available data to conduct their studies. These data include firm-level data collected from government agencies such as the US Securities and Exchange Commission (e.g., Bao & Datta, 2014), conference calls (e.g., Huang et al., 2018), patents (e.g., Kaplan & Vakili, 2015), and other data collected through independent data and analytics service providers such as Crunchbase (e.g., Shi et al., 2016) and Investext Plus (e.g., Giorgi & Weber, 2015). Social media platforms such as Facebook (e.g., Bapna et al., 2019), Twitter (e.g., Hu et al., 2019), and Gowalia (e.g., Lee et al., 2016), as well as other community-based discussion boards (e.g., Huang et al., 2019; Samtani et al. 2017), are also common data sources utilized by authors.

Collecting unstructured, textual data from host organizations is not a trivial task. Consequently, researchers have adopted a variety of approaches to gain access to and
collect those data. Especially in the case of social media and other community-based discussion boards and blogs, researchers needed to rely on web crawling techniques (e.g., Hu et al., 2019; Lash & Zhao, 2016) or use the platform-enabled Application Programing Interfaces—APIs (e.g., Bapna et al., 2019; Geva et al., 2019; Lee et al., 2016). Both of these approaches come with salient challenges, as reported on by the researchers in our sample. For instance, Bapna et al. (2019) explain the limitations of relying on the Facebook API to collect posts: “For some firms, we were not able to gather posts all the way back to the date the firm joined Facebook, possibly because of restricted access settings by some firms, or limits set by Facebook on historic data” (p. 435). Similarly, researchers who rely on web crawlers may face limitations and risk inconsistencies in the data due to restrictions imposed by the websites and platforms. Samtani et al. (2017), for example, highlight such restrictions and describe how they were forced to develop a specialized parser to circumvent a forum’s anticrawling mechanisms.

Some papers in our sample (e.g., Bapna et al., 2019; Samtani et al., 2017) try to alleviate some of the limitations imposed by data hosts and platforms. For example, some studies employ multiple methods and collect data from multiple sources to increase confidence in the data collected. This is exemplified by Lash and Zhao (2016) in describing their data collection strategy: “We picked two popular and complementary sources—IMDb and Box Office Mojo. [...] IMDb has an application program interface (API) to provide movie data. The data from Box Office Mojo can only be obtained by the public from its web pages. To get a more comprehensive data set, our system employs two scripts: one interacts with APIs, while the other is a web scraper to retrieve and parse HTML data from web pages” (p. 879). Other researchers adopt workarounds to alleviate the web crawling limitations. For example, Haans (2019) scraps all the texts on the front pages and on the pages one click deeper on the same domain. Unfortunately, several other articles in our sample neither acknowledge nor provide any evidence of their attempt to alleviate challenges during data collection.

Given the unstructured nature of data sources, one of the most critical steps in applying algorithmic intelligence is preparing the data and organizing them into a format
that algorithms can read (also known as preprocessing). Though not recognized as a
distinct phase in extant literature, we report our findings about data preparation separately
(from data collection) to highlight the potential implications. In general, researchers may
undertake a range of different preprocessing steps to prepare the data for analysis. In the
case of topic modeling, researchers typically engage in practices of selecting, filtering,
normalizing, and evaluating terms.

First, most topic models require a “document term matrix” as input data, which
specifies how many times a specific word or term occurs in a specific document.
Researchers thus need to decide on what actually counts as a term. Based on the
assumption that terms in a text are split by whitespaces, researchers typically construct
term lists for documents by breaking up the text every time a whitespace character is
encountered. In doing so, researchers typically remove characters such as numbers and
punctuation that do not actually represent words. While this process of “word
tokenization” seems like a trivial process, researchers actually need to make important
choices. For example, should a word such as “data-driven” be split up into two words
“data” and “driven,” or be merged as “datadriven”?

Second, researchers may decide that not all terms are equally relevant. For
example, terms such as “the” and “be” are frequently occurring words that often carry
little actual meaning. In most studies in our sample, such “stop words” are removed by
researchers in the process of cleaning the data for analysis. Next to removing “standard”
stop words, some researchers go out of their way to identify additional stop words, or
choose to remove (combinations of) terms that may be considered non-meaningful in
their specific research context. For example, some papers in our sample remove
disclaimers from texts before feeding them into the topic modeling algorithm. Beyond
removing stop words and high-frequency words or phrases, researchers may also remove
words that are actually very rare or infrequent.

Third, researchers may put effort into normalizing terms, i.e., by converting two
seemingly distinct terms that originate from the same verb or noun to a standardized
version. The most common forms of normalization are stemming and lemmatization.
Stemming refers to when you “strip off any affixes” of words and are left with the stems of those words (e.g., “modeling” becomes “model”) (Bird et al., 2009, p. 107). Doing this can result in lists of words that are not actually in the dictionary (e.g., when “analyzing” becomes “analyz”). Lemmatization overcomes this challenge by normalizing words to a valid base form (e.g., “analyzing” becomes “analyze” when labeled as a verb) (Bird et al., 2009). Researchers also need to decide how to distinguish verbs from nouns as input for the lemmatizer. Researchers may simply decide to treat all words as either verbs or nouns, or adopt algorithmic approaches such as (pre-trained) point-of-speech taggers to help them (see Bird et al., 2009). Still, the task of distinguishing verbs and nouns is not easy (for example, how to tell whether “machine learning” is a verb or a noun). Another thing that researchers might do is standardize abbreviations and their full counterpart (e.g., BI and Business Intelligence). Additionally, researchers may combine frequently occurring combinations of words or n-grams that reflect a distinct concept (e.g., “machine learning” and “return on investment”). With regard to normalization practices, we see that quite a number of studies in our sample applied stemming, which is evidently more popular than lemmatization. However, abbreviations are hardly considered in our sample, and n-grams seem not to be considered at all.

Before feeding the document-term matrix into the algorithm, researchers might still first evaluate terms by assigning higher weights to terms that are seemingly more important or distinctive than others. Some topic modeling algorithms such as LSA and NMF allow for the term-document matrix to be weighted using TFIDF. Note that LDA does not allow for pre-weighting the term-document matrix and, as most papers in our sample apply LDA, this step is not typically performed.

5.10.2.3 Data Analysis

Implementing an algorithmic approach is not a straightforward task and, even after settling on one particular algorithm, researchers still need to make important decisions about the tools and model parameters that may affect the results. First, researchers need to decide which tool(s) they are going to use—tools may differ in their assumptions and underlying implementation. Second, researchers need to decide how to set the input
parameters, i.e., the primary constants and initialization settings of the algorithm. In the case of topic modeling, researchers need to decide on the number of topics as one of the crucial input parameters, although “[h]ow to determine the appropriate number of topics is an area of ongoing research and debate” (Giorgi & Weber, 2015, p. 350). Additional parameters for topic modeling algorithms might include, for example, the initialization procedure, learning method, accepted error, and number of iterations. Optionally, researchers may also set a random seed to ensure replicability of the model.

In addition to generic input parameters, researchers also need to consider parameters that are specific to the chosen algorithm. For instance, in the case of LDA, researchers need to determine the values of the hyperparameters, i.e., parameters that represent assumptions about how many topics are typically contained in one document, and how many words are typically associated with one topic (Binkley et al., 2014). Depending on the tool that is being used, many more parameters may be set and even after having trained a model, researchers may still define a number of output criteria. For example, some researchers set a threshold when assigning topics to documents, while other researchers drop topics when they do not comply with some criterion of significance.

The choice of parameters is crucial as the model outputs are sensitive to these parameters. Based on our analysis, we identified common themes regarding how researchers justified their choice of parameter settings in this phase of data analysis.

5.10.3 Appendix C3: Evaluation Criteria for Findings

We extensively coded all the 40 articles in our sample based on our coding scheme. This resulted in each article being coded for each of the research phases, with reference to the choices they made, how they justify those choices, and how they validate those choices. In an intermittent stage we identified emergent themes to structure our findings for each phase. Next, we abstracted higher order themes that cut across several research phases to

30See for example the Python Gensim documentation at https://radimrehurek.com/gensim/models/ldamodel.html
present our findings parsimoniously. The three themes reported in the main text: lack of explicit description, contentious justification, and polarized, partial, or no validation, are those abstracted themes.

For the purpose of transparency, we reported our assessment of each of the papers in our sample in the form of four criteria in Table 2 in the main text. These criteria correspond to the three abstracted findings. Criteria 1 and 2 correspond to the first finding of lack of explicit description, criterion 3 corresponds to the second finding of contentious justification, and criterion 4 corresponds to the third finding of polarized, partial, or no validation.

**Criterion 1.** We assessed each of the papers in our sample based on the extent to which they are transparent about their choices into three levels – Low, Medium, and High. Transparency of choices was assessed for all the stages except final model validation. We assigned the Low score to those papers that barely describe how they collected the data, barely narrate whether they applied any preprocessing steps, barely describe their parameter specifications, and are also not explicit about research design choices. The High scores signify that the papers are fairly transparent about most (not all) of the important choices, while the Medium scores signify everything in between.

**Criterion 2.** This criterion is at the intersection of transparency and justifications in that we assessed the papers based on the extent to which they are transparent about justifying their choices. In other words, in this criterion we still assess whether authors justify their choices and not the nature of justifications per se. Again, this criterion applies to all the phases of research except final model validation. The key choices that papers need to justify include their research design choices (e.g., why did authors apply LDA algorithm as opposed to alternative choices), data analysis choices (e.g., why did authors select a particular number of choices), as well as data preparation choices (e.g., why did the authors remove low frequency words). If a paper justifies these choices (irrespective of validity of justification), they will get a High score, whereas those that do poorly in justifying these choices will get a Low score. All others will get a Medium score. It is noteworthy that our evaluation criteria are hierarchical in nature. This means that Criterion 2 will only be applied to the limited choices for which the paper was
transparent in Criterion 1. Accordingly, hypothetically, if there are fifty choices made in a particular study, out of which the paper only describes five explicitly, the paper will get a Low score in Criterion 1. But, if the paper justifies all of those five choices, it will get a high score in Criterion 2. We followed this approach to make sure that a paper that has been punished once, does not get punished over and over again. Hence, our current approach is conservative in demonstrating the state of severity of the problem in the prevalent practices.

**Criterion 3.** In this criterion, we assessed the nature of justifications provided by the papers, which could range from Not Applicable (NA), Partial, or Thorough. A score of NA means that the paper is not transparent about most of the justifications. Hence, if the paper does not justify any choices, it is not possible to evaluate the justification at all. The papers that provide detailed, non-contentious justifications for most of their choices will get the score of Thorough. All other papers will get a score of Partial, where some justifications are satisfactory, but some others are contentious. Again, it is noteworthy that this is also a hierarchical criterion. Going back to our earlier example, if there are 50 choices to be made and, out of those, a paper is transparent about five of them, it will get a Low score in Criterion 1. If the paper justifies two out of five choices, it will get a Low score in Criterion 2. But if those two justifications are not contentious, the paper will get a Thorough score in Criterion 3, though the net score on Criterion 3 might be lower as it provides valid justification only for two out of 50 possible choices.

**Criterion 4.** In this evaluation, we assessed the papers based on how they validate their choices. This is not a hierarchical criterion as it is mainly the assessment of the final model validation practices. As described in the main text, authors could validate their final model by validating the semantic quality of topic models, performing sensitivity analysis, comparing with other methods, and comparing with external information. Within each of these four categories, again there are multiple approaches through which the validation checks could be performed. If the paper validates the final model by somehow evaluating the model quality, performing some sensitivity analysis or at least comparing with other methods, and by comparing with external information, it will get a score of Thorough. Conversely, if the paper hardly performs any validation checks, it will
get a score of Hardly. Everything in between will get a score of Partial.

The purpose of providing this assessment in our paper is to help the readers understand the state of prevalent practices more clearly. It is definitely not intended to pin-point any particular paper in the practices they followed. Topic modeling is a complex method and it is not possible to cover each aspect of the paper in our assessment and hence we caution the readers from over-generalizing about the quality of the paper based on this assessment.

5.10.4 Appendix Tables

Table C1.1: Abstracted Coding Scheme

<table>
<thead>
<tr>
<th>Phase</th>
<th>Particular</th>
<th>Description and Sample Questions</th>
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<tbody>
<tr>
<td>Research Design</td>
<td>Purpose of the Paper</td>
<td>Examples include Designing and testing methodology, system development and measure development.</td>
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<td>Use of Algorithmic Intelligence</td>
<td>Why do the authors use automated text analysis to achieve the purpose of the paper?</td>
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<td>Methodological Approach</td>
<td>Whether authors rely on supervised or unsupervised learning and why?</td>
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<tr>
<td></td>
<td>Method</td>
<td>Why do the authors rely on topic modeling?</td>
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<tr>
<td></td>
<td>Type of Topic Modeling Algorithm</td>
<td>Which topic modeling algorithms authors use? Examples include LDA, NMF, LSA, PLSA, LSI, and STM. How do they justify choice of a particular algorithm?</td>
</tr>
<tr>
<td>Data Collection and Preparation</td>
<td>Type of Data</td>
<td>Examples include proprietary or publicly accessible data.</td>
</tr>
<tr>
<td></td>
<td>Data Collection Approach</td>
<td>How the data were collected? Examples include web crawling, accessing through API or obtaining company database.</td>
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<tr>
<td></td>
<td>Sampling Criterion</td>
<td>Whether authors are explicit about the sampling criteria? How do they justify it?</td>
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<tr>
<td></td>
<td>Overall Preprocessing Steps</td>
<td>Are the authors explicit about the need for data preparation in context of topic modeling?</td>
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<td></td>
<td>Removal of Words / Phrases</td>
<td>How do the authors justify removal of words and phrases including removal of stop words, removal of context specific words, removal of low- and high frequency words, and removal of duplicate phrases or texts?</td>
</tr>
<tr>
<td></td>
<td>Other Steps</td>
<td>How do the authors justify steps such as removal of non-alphabetic characters, pre-weighing terms, stemming, lemmatization, and identification of bigrams or n-grams?</td>
</tr>
<tr>
<td>Data Analysis</td>
<td>Parameters</td>
<td>How do the authors set various parameters including number of topics, hyperparameters, number of iterations, convergence benchmark, learning methods, topic-document thresholds, and random seed? How do they justify choices of each parameter?</td>
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<tr>
<td>Overall</td>
<td>Are the authors explicit about the need for validation in context of topic modeling?</td>
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<tr>
<td>Topic Selection</td>
<td>Do the authors drop some irrelevant topics from the final list based on human interpretation? How do they justify the same?</td>
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<tr>
<td>Evaluation of Topic Quality</td>
<td>Do the authors validate the quality of topics in the final model? Examples of such validation include humans labeling and checking topics or use of computational measures including topic coherence and cluster quality.</td>
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<tr>
<td>Topic-Document Allocation</td>
<td>Do the authors validate topic-document allocation? Examples of such validation include humans checking appropriateness of allocation or use of statistical measures.</td>
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<tr>
<td>Sensitivity Analysis</td>
<td>Do the authors perform sensitivity analysis to validate the model output? Examples of such sensitivity analysis include comparing outcomes by altering parameters, by using left-out sample, or by including back the dropped topics.</td>
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<tr>
<td>Comparing Competing Models</td>
<td>Do the authors validate the model output by comparing it with the competing models. Examples of such validation include manual or computational comparison among competing topic modeling algorithms, with different text-mining algorithms, and with non text-mining statistical methods.</td>
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<tr>
<td>Comparing with External Information</td>
<td>Do the authors validate the model output by comparing with the industry trends? Examples of such comparison include visual interpretation by humans or use of statistical measures to establish correlations.</td>
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Chapter 6

6 Conclusions and Future Research

6.1 Discussion

This thesis examined the phenomenon of organizing in- and for- the digital age with specific focus on the Indian banking industry as well as on the implications for work practices of academic researchers. In the form of three essays, it focused on distinct facets of the phenomenon.

Essay 1 (Chapter 2) focused on the aspect of organizing for the digital age from the perspective of industry by examining the impact of a policy change on ability of financial organizations to capture value through their digital innovations. In particular, the study exploited the India’s 2016 demonetization policy as an exogeneous policy shock to understand and explain its consequences on the value capture by Indian financial organizations due to the discontinuity in Indians’ trust in money (cash currency in particular). The study constructed a novel dataset of digital currency transactions of various financial organizations including a panel dataset of 46 large Indian banks’ electronic payments transactions (debit card payments at merchant outlets), a timeseries dataset of India’s largest stock exchange (Bombay Stock Exchange) with data on local stocks and gold ETF transactions, and a timeseries dataset of India’s prominent Bitcoin organization (LocalBitcoins) with data on India level Bitcoin transactions. Using the regression discontinuity design, the study provided causal evidence of heterogeneity in financial organizations’ ability to capture value through their digital offerings amid the discontinuity in trust in cash currency. Specifically, the study demonstrated that demonetization triggered trust discontinuity which had a spillover effect on financial organizations; the organizations at arm’s length from the government were able to capture more value than their counterparts. This was an unintended consequence of the demonetization policy implemented by the government as it resulted in value slipping from the government organizations to the private ones.
In addition to the discussion included in Chapter 2, Essay 1 opens up interesting avenues for future research. First, the findings from the study can be extended to examine other environmental jolts (e.g., Sine & David, 2003) that might trigger large scale digitization. For instance, the current COVID-19 infused pandemic is a good case in point. Such exogeneous shocks might lead to a permanent shift toward digitization across industries and geographies and yet there is a plausible scenario of the markets going back to the pre-shock levels of digitization once the effect of such shocks vanish. For instance, the recent announcement about the discovery of a COVID-19 vaccine by Pfizer triggered the stocks of Zoom, a prominent virtual meetings platform, to tumble by around 20% (Winck, 2020), though it remains to be seen as to what extent the stock market sentiment is a reflection of the actual usage of Zoom. Second, another interesting avenue for future research could be examining which firms are more resilient to withstand such shocks like demonetization or COVID-19 and are able to consistently capture more value through their digital innovations vis-à-vis the firms that struggle to do so. Third, a limitation of the current study of not measuring the trust in money directly could be an opportunity for future research. In fact, along with the coauthors, I have started exploring this direction a by developing a data-driven measure of trust using textual data from Tweets and by analyzing the data using computational techniques including sentiment analysis and topic modeling. I intend to develop this auxiliary analyses into a full manuscript in future.

Essay 2 (Chapters 3 and 4) focused on the aspect of organizing in the digital age from the perspective of industry, examining the informing practices (Schultze, 2000) of data science professionals as they perform rationality (Cabantous & Gond, 2011) to facilitate decision-making in organizations. In particular, the study focused on the work practices of data science professionals in three large Indian banks. The study demonstrated that the data science professionals enact the informing practices by inscribing expertise into models and insights, and prescribing insights for rational decision-making. They make several salient choices while enacting these practices, and the choices are influenced by the context of problem-solving processes, sometimes imposing paradoxical tensions on the practices of inscribing expertise and prescribing
insights. The study also uncovered a few mechanisms that data science professionals adopt to embrace the paradoxes by triggering the attention of business professionals. This study provided a nuanced understanding of data science in practice that has implications for organizational decision-making processes.

I discuss two avenues that can be pursued in future research based on my study. First, in my study I observed that organizations adopt distinct design in organizing their data science units. Some integrate data science under established functions (e.g., marketing departments having their own data science teams), while others set data science up as independent units (e.g., a center of excellence in the corporate hierarchy). Though not systematically analyzed, my data do imply the consequences of such design choices on the nature of decision-making. Future research can unpack these implications by theoretically sampling such organizations with distinct designs and there by contribute to the organization design literature (e.g., Puranam et al., 2012). Second, my study sets the founding stones for a potential extension of the garbage can model of organizational choices (GCM) of organizational choice (Cohen et al., 1972). In particular, my study demonstrates an important role of data science professionals as distinct agents, over and above managers, in decision-making processes. Accordingly, there is an opportunity to extend the GCM by factoring in the role of data science professionals.

Essay 3 (Chapter 5) focused on the phenomenon of digitization from the perspective of work practices of academic researchers as they increasingly rely on algorithmic intelligence in their studies. In particular, the study conducted a methodological review of prevalent practices of adoption of topic modeling in academic research by focusing on articles published in top-tier IS and management journals. The findings from this critical methodological review demonstrate several problematic practices concerned with academic rigor including lack of explicit description, contentious justifications, and polarized, partial, or no validation. These practices in applying topic modeling in academic research pose challenges for academic rigor in terms of reliability, validity, and generalizability. The study proposed a framework to alleviate some of the challenges identified. The framework was proposed to invoke
mindful evaluations among the scholars pursuing algorithmic intelligence in their research. It was intendedly kept open by posing questions, instead of providing answers, to ensure that it is not treated as yet another best practice tool, an approach that the study itself criticizes.

This study also opens up some avenues for future research. First, a natural extension of the study would be to conduct interviews of some of the authors of the papers that were reviewed in the sample. By including the authors’ perspectives, one can unpack the nature of the review process and understand how the review process as well as the space constraints might have influenced the practices reported in the published papers. Such interviews may provide a chance for the reader to peek into the review process and hence may be able to propose specific recommendations for the editors and reviewers on handling papers that use algorithmic intelligence. Second, this study focused on topic modeling as an exemplar of algorithmic intelligence-based approaches being adopted in academic research. Future studies can potentially conduct similar review of other computationally intensive tools, for instance, sentiment analysis. By conducting more studies in this space, we can build broader knowledge about algorithmic intelligence in academic research and thereby guide academic scholars in using such tools better.

6.2 References


Curriculum Vitae

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Education

PhD in Business Administration / Information Systems (expected Spring 2021)
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Master of Business Administration / Marketing (March 2004)
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Honors and Awards

Runner-up, Best ERF Paper Award, AMCIS, USA (virtual) (Aug 2020)
Dean’s Conference Scholarship, Ivey Business School (Sep 2019-Aug 2020)
Brock Scholarship (Sep 2019-Aug 2020)
Best Student Paper Award, Pre-ICIS SIGDSA Symposium, Germany (Dec 2019)
Honorable Mention Award in OT Division, ASAC, Canada (June 2019)
Professor Al Mikalachki PhD Research Fund (Jan 2019)
Travel Grant for OMT Workshop, UBC, Canada (Feb 2018)
Best Paper Award in Strategic IT Track, AMCIS, USA (Aug 2018)
Runner-up, Best Poster Award at Ivey Faculty Retreat (May 2017)
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Work Experience

Doctoral Fellow, Scotiabank Digital Banking Lab, Ivey (June 2018-Jan 2021)
Sub-unit Head, Branch Control Unit, HDFC Bank Ltd., India (Sep 2006-July 2016)
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Selected Peer-reviewed Conference Presentations and Proceedings


