Understanding the Big Data Analytics Deployment Gap: Operationally Leveraging Big Data Analytics Capability for Value Generation in Healthcare

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Abstract

Despite the surge of big data analytics (BDA) deployments in healthcare, many organizations still struggle to successfully realize value from their investments. This has resulted in the phenomenon of BDA deployment gap, where relative to the interest and investments in BDA initiatives by the organizations, actual value generated from successful migrations of BDA models from data labs to in-practice environment deployments at the initiative level have been scarce. To leverage the growing repository of big data, organizations are required to develop the ability to collect, store, process, and analyze big data (BD); this process is referred to as big data analytics capability (BDAC) in the literature. However, the underlying assumption that organizations with BDAC will always be able to orchestrate the necessary resources and capabilities to use the information from analytics to generate value largely ignores the operational mechanisms involved in how the information is leveraged. This thesis seeks to address this gap in the literature by investigating how organizations find ways to operationally leverage BDAC to generate value in the context of healthcare and generating a better understanding of the knowledge management practices involved in transforming the information from analytics into BDA-enabled capabilities that can lead to improved operational and clinical outcomes.

This thesis includes three components. First, the constructs involved in the value generation process from BDAC in the general context are identified: BDA resources, BDAC, and value. Second, a systematic literature review (SLR) is conducted to develop the conceptual framework in the healthcare context and identify the possible constituents of the mediating ‘black box’, which serve as the operational mechanisms in the leveraging process of BDAC in generating value. Finally, a multiple case study is presented to empirically validate the presence and explicate the workings of the ‘black box’ presented in the indirect value generation
pathway framework via BDA-enabled functioning capability (BDA-eFC), a dual-purpose capability. The study further supplements the BDAC literature by offering a nuanced understanding of the underlying mechanisms of how organizations implement BDA in the healthcare delivery process at a functional level to generate value, and address the BDA deployment gap in the healthcare context.

Keywords

Big Data Analytics (BDA), BDA Deployment Gap, BDA Capabilities, Healthcare, Systematic Literature Review (SLR), Multiple Case Study
Summary for Lay Audience

With the digitization of healthcare, various healthcare organizations have been investing in ways to use the large volumes of data generated (e.g., electronic health records) to improve the quality of care, patient experience, and overall cost of care. The large volumes of data, often referred to as big data (BD), have been predicted to deliver on the promise of immense benefits for healthcare organizations through the use big data analytics (BDA), which can provide unprecedented ways to gain insights for decision-making that were not possible by the traditional methods in healthcare. In the pursuit of these promises, healthcare organizations invest considerable resources towards developing BDA capability (BDAC) and deploy various BDA initiatives; however, many organizations fail to successfully realize the intended value from the deployments. Often, the healthcare organizations are left with plenty of information that can be used and are not always useful. The existing research in the context of healthcare offers limited understanding on the leveraging mechanisms involved in transforming the information from BDA into insights and knowledge that enables improved work efforts in the care delivery process, which ultimately leads to value.

This thesis seeks to address this gap through an examination of healthcare organizations that have deployed various BDA applications and possess BDAC to better understand how these organizations leverage the information generated from BDA to inform their decisions and actions to change care practices and improve healthcare delivery services. As a result, this research finds consistent patterns of BDA-enabled routines and practices that help facilitate the effective leveraging of information outputs from BDA in the value generation process in healthcare. It also highlights the importance of these leveraging mechanisms in linking the healthcare organizations’ BDAC with ways to improve or innovate the operational processes involved in the delivery of care.
Dedication

For my parents,
Robert Shin & Jenny Park
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# Table of Contents

Abstract............................................................................................................................................. i
Summary for Lay Audience.................................................................................................................. iii
Dedication............................................................................................................................................... iv
Acknowledgement ............................................................................................................................... v
Figures................................................................................................................................................... x
Tables .................................................................................................................................................... xi

Chapter 1 .............................................................................................................................................. 1

1. Introduction......................................................................................................................................... 1

1.1 Key Concepts ................................................................................................................................... 4
  1.1.1 Big Data (BD) ........................................................................................................................... 5
  1.1.2 Big Data Analytics (BDA) Resources ....................................................................................... 6
  1.1.3 Big Data Analytics Capability (BDAC) .................................................................................... 8
  1.1.4 Information, Insights, and Knowledge ...................................................................................... 9

1.2. Healthcare Context .......................................................................................................................... 10
  1.2.1 Introduction ............................................................................................................................. 11
  1.2.2 Challenges in Healthcare OM ................................................................................................. 12
  1.2.3 Applications of BDA in Healthcare ......................................................................................... 19

1.3 Overarching Research Objective and Question............................................................................... 22

Chapter 2 .............................................................................................................................................. 24

2. Literature Review ............................................................................................................................... 24

2.1 General Background ........................................................................................................................ 25
  2.1.1 Big Data Analytics Capability (BDAC) ................................................................................... 25
  2.1.2 Value of BDA .......................................................................................................................... 29
  2.1.3 Conceptualizing BDAC to Value ............................................................................................ 30

2.2 Theoretical Background .................................................................................................................. 33
  2.2.1 Resource-based View (RBV) ................................................................................................... 33
  2.2.2 Dynamic capabilities view (DCV) .......................................................................................... 35
  2.2.3 Knowledge-based View (KBV) and Knowledge Management (KM) ...................................... 36

2.3 The ‘Black Box’ .............................................................................................................................. 38

Conclusion ............................................................................................................................................ 41

Chapter 3 .............................................................................................................................................. 42

3. Systematic Literature Review (SLR) ................................................................................................. 42

3.1 Introduction ....................................................................................................................................... 42

3.2 Methodology .................................................................................................................................... 43
  3.2.1 Step 1: Identify the Purpose and Frame the Research Questions ........................................... 43
  3.2.2 Step 2: Determine the Inclusion/Exclusion Criteria ................................................................. 44
  3.2.3 Step 3: Determine the Search Procedures .............................................................................. 46
  3.2.4 Step 4: Select the Pertinent Literature and Create Synthesis Sample .................................... 48
  3.2.5 Synthesize the Literature ....................................................................................................... 49
  3.2.6 Report the Findings and Results ............................................................................................. 51

3.3 Results ............................................................................................................................................. 54
5.3 Future Research

5.3.1 Value Capture from BDAC
5.3.2 Factors that Impact the Enacted Decisions and Actions by End-users
5.3.3 Application of BDAC to Value Framework to Specific BDA Forms and Types

Chapter 6

6. Reference & Appendices

A. Systematic Literature Review Keyword Search Command
B. Multiple Case Study Research Protocol

Curriculum Vitae
Figures
Figure 1. Classification of big data resources adopted from Gupta and George (2016)...........8
Figure 2. Classification of BDA resources that serve as antecedent to BDAC ..................28
Figure 3. Direct value generation pathway view of BDAC to value relationship .................31
Figure 4. Indirect value generation pathway view of BDAC to value relationship ...............32
Figure 5. Conceptual framework of the mediating operational black box in the BDAC to
value relationship in the value generation pathway .................................................40
Figure 6. Six-step review process for the systematic literature review ............................43
Figure 7. BDAC to value framework in healthcare (indirect value generation pathway
through the functional capabilities) ............................................................................71
Figure 8. Replication approach to the multiple case study ...........................................91
Figure 9. Qualitative data structure of the process of knowing steps ...............................110
Figure 10. Description of the interactions and strength of the engagements of each process of
knowing steps ............................................................................................................112
Figure 11. KM-structuration model of BDAC to value mediated through BDA-eFC in
healthcare ...................................................................................................................143
Figure 12. The ordinary and dynamic capability role of BDA-eFC in mediating the
relationship between BDAC and value with the value generation pathway in healthcare ....145
Figure 13. Multilayer capabilities framework of BDAC and BDA-eFC at firm level and
functional level in healthcare .....................................................................................146
Tables

Table 1. Examples of real-world applications of BDA healthcare.................................20
Table 2. List of definitions of BDAC and theoretical lens adopted in the extant literature.....25
Table 3. Criteria for including or excluding papers in the systematic literature review.......44
Table 4. Number of returns from selected searchesa ..........................................................48
Table 5. Categories and sub-categories used for data extraction and analysis in the systematic literature review ........................................................................................................50
Table 6. Aggregated summary of the reviewed papers based on the synthesized categories .52
Table 7. Application of theoretical lens for each research stream category......................55
Table 8. Characteristics of the healthcare organizations in the multiple case study based on number of beds, medical staffs, and hospital characteristics .........................................................93
Table 9. Distribution of the informants per healthcare organization and total number of interviews per roles ........................................................................................................94
Table 10 Use cases of BDA deployments for each healthcare organization......................99
Chapter 1

1. Introduction

The saliency of big data (BD) can be observed in how people and organizations engage in day-to-day activities involving technologies that continuously collect, store, process, and analyze large amounts of data. With technological advancements, these interactions occur at larger scales, faster rates, and in diverse formats, which have been motivating the transition towards the BD era. These facets directly relate to the prevalence of the ‘3Vs’ of BD: volume, velocity, and variety in the literature and practice (Chong et al., 2016; McAfee and Brynjolfsson, 2012). Although the characteristics of BD have been a topic of interest in the past, the emergent discussions have taken a pivot from focusing on defining what BD is towards the topic of intelligent BD, which emphasizes the insights generated from BD (George et al., 2014), thus, moving beyond the technical aspects of BD towards understanding ‘how’ to leverage BD to reveal insights that can generate value.

BD has become one of the most discussed research topics in the last decade by both scholars and practitioners, and Operations Management (OM) research is no exception (Choi et al., 2018; Lamba and Singh, 2017). Potential opportunities and benefits offered by BD are vast, where through effective analysis of the data, organizations can identify multiple potential value generation pathways. This type of analysis is referred to as big data analytics (BDA). An organization’s capacity to leverage BDA is seen as a valuable capability required to stay competitive with the exponentially increasing availability of data, and many organizations seek to find ways to create value from BDA (Choi et al., 2018; Wamba et al., 2017).

The potential value of BDA has been an important topic of discussion in healthcare research, highlighted by the large increase in the number of review papers on BDA in
healthcare published in management and healthcare literature in the last five years (Brossard et al., 2022; Dash et al., 2019; Galetsi and Katsaliaki, 2020; Kamble et al., 2019; Khanra et al., 2020). Opportunities to leverage BDA in healthcare operations continue to grow with the increasing number of healthcare data from Electronic Health Records (EHR), patient summaries, sensors and information on well-being, behaviour and socio-economic indicators, hospital operational data, and telemedicine (Pastorino et al., 2019). BDA-based value has been expected to range from $350 billion to $410 billion annually by 2025 in the US alone through effective care delivery, enhanced clinical productivity, reduction in variability and waste, consumer-focused sites (shift towards outpatient and home setting care visits), and improvement in nonclinical efficiencies (Singhal and Carlton, 2019). These benefits can be attained at different levels of the healthcare systems, branching from organizational strategy to patient-level care quality, mainly through better informed decision-making. Healthcare organizations are cognizant of these potential opportunities; this is evident in the increase of 232% ($8.5 to $28.3 billion) in pharmaceutical and biotech investments and the 186% ($10.8 to $30.8 billion) increase in health tech and digital health investments from 2010 to 2018, which signals a considerable increase in deployments that specifically seek to leverage the digital assets and platforms in healthcare (Singhal and Carlton, 2019).

While the perceived potential value of BDA has compelled many organizations to invest in and adopt BDA, stories of successful implementations and realization of actual value have been relatively scant (Vidgen et al., 2017; Wiener et al., 2020). According to a study by Wavestone (2022), in which executives of 94 blue-chip companies were surveyed, 40.6% of the companies’ BDA strategies had yet to generate success and 47% of the corporate data strategies had failed to achieve business value. Considering that approximately 92% of the participants reported that the investment in data and AI is increasing, the rate of failure is of
managerial concern. Of the 94 participants in the survey, 21% were from the healthcare industry, which was the second largest represented industry next to financial services (60%). To supplement this data, Castellanos et al., (2019) conducted a survey of 76 participants that have participated in BDA projects and found that only 23.6% had an active BDA program and 47% had only developed between 1 to 3 BDA projects. These numbers demonstrate that despite the growth in the interest of organizations in BDA adoption, the number of implemented deployments is limited and lacks successful value generation.

A phenomenon where organizations observe a discrepancy in the actual BDA deployments compared to the expected interest and investments in BDA is known as BDA deployment gap (Chen et al., 2017). The BDA deployment gap can be observed at an organizational level, but initially stems from the initiative-level BDA deployment gaps, whereby successful migration of BDA models from the data laboratory into a real-world environment that generates value is scarce. With such large up-front costs and high risks associated with BDA deployments, organizations can greatly benefit from understanding this gap in the BDA to value generation pathways (Mikalef et al., 2018), especially in healthcare, where resources are typically constrained (Singh et al., 2021). Although the healthcare industry has lagged behind other sectors, such as financial services and retail—likely due to industry-specific constraints related to patient confidentiality, resources, and high standards of quality—the process of digitization in healthcare systems has already begun, and continuous interactions with BDA is inevitable.

As healthcare organizations have transitioned into the digital era, healthcare data and e-health have been essential components in the way healthcare is provided, and the use of BDA applications continues to grow in healthcare (Galetsi and Katsaliaki, 2020; Kamble et al., 2019). Application of BDA in healthcare provides a wide range of opportunities and benefits (Singh
et al., 2021), and the value often comes in the form of informed decision-making ability from the insights generated via analytics (Dash et al., 2019; Janssen et al., 2017). The extant management literature has adopted various frameworks that focus on the examination of BDA resources (e.g., tangible, intangible, and human skill resources related to BDA) and the ability to capture and analyze data to generate insights, referred to as BDA capability (BDAC) (Mikalef et al., 2017; Wang et al., 2018c), but it lacks an understanding of the leveraging mechanisms of BDAC to generate value.

To address the BDA deployment gap in healthcare, it is necessary to identify the operational leveraging mechanisms that entail the conversion of BDA-based information outputs from BDAC into the generation of insights and understanding that lead to better informed decisions and actions that can produce improved practices and routines. Particularly, with healthcare organizations that have already developed BDAC and still fail to generate value from their BDAC, the question of how BDAC can be leveraged to address the BDA deployment gap for value generation in healthcare is of urgent interest. Finally, investigating the interactions between the technological structures and human agents in the healthcare organization in BDA-based value creation processes will provide a better understanding of the knowledge conversion and application processes that lead to functioning improvements that impact the operational system from BDAC.

1.1 Key Concepts

Definition of some concepts discussed in the previous section is still evolving in the literature; however, it is important to have a clear understanding of certain concepts that will be used throughout this thesis, specifically, BD, BDA resources, and BDAC. In addition, terminologies such as data, information, insights, and knowledge will be used frequently in the examination
of the research problems. This section will briefly discuss these concepts and terminologies, which will be elaborated in further detail in Chapter 2.

1.1.1 Big Data (BD)

Several definitions of BD have been discussed in the literature to draw a clearer distinction between BD and traditional data. The majority of practitioners and scholars have emphasized the “three Vs” as the characteristics that define big data: volume, variety, and velocity (Bharadwaj, 2000; McAfee and Brynjolfsson, 2012; Mikalef et al., 2018). Volume refers to the size and quantity of the variables and observations in an aggregated dataset. Although the size at which a dataset is considered big data has not been explicitly defined, the general consensus is that big data is represented in petabytes or exabytes (Lamba and Singh, 2017). Variety refers to the multitude of structured, unstructured, and semi-structured forms of data sources. Unlike the traditional form of structured data, big data can be in forms of text, audio, images, and videos. Velocity denotes the speed at which the data is generated, collected, updated, and becomes obsolete (Mikalef et al., 2018). The speed at which big data can be viewed and processed is in real to near-real time.

In addition to the aforementioned characteristics, some scholars also refer to veracity (Belle et al., 2015) and value (Fosso Wamba et al., 2015) as characteristics of big data. Veracity refers to the reliability of big data and its degree of authenticity, privacy, and protection from unauthorized access. The quality and reliability of the data directly relates to the accuracy of the analysis and the decisions that follow (Kamble et al., 2019). Often, value has been stated as the objective of using a BD application or its impact on performance. It is important to acknowledge that the definition of BD is still developing; it can have more characteristics based on context and the boundary conditions are dynamic in nature and contingent on various factors such as the size of the firms, geographical location, and industry.
1.1.2 Big Data Analytics (BDA) Resources

The terminologies *BDA resources* and *BDA infrastructures* have been used interchangeably in the extant literature as the antecedent to BDAC (Grover et al., 2018; Wamba et al., 2017a). BDA resources are comprised of tangible, intangible, and human resources (Gupta and George, 2016). Tangible resources include data from external sources, internal sources, or a combination of the two (e.g., transactional data, user-generated data, electronic health data) and analytic platforms that can collect, store, integrate, process, share, and manage BD. Some examples of the various technologies used are Apache Hadoop, MapReduce, and NoSQL, which can be quite accessible for organizations.

Human resources refer to the high degree of expertise and skills required from the managerial level to design and implement BDA strategies that align with the business strategy and the technical skills of the big data professionals (e.g., data specialists) to precisely execute the strategies. BDA professionals should have competencies in skills such as machine learning, data extraction, handling large data sets in unstructured and structured forms, statistical analysis, coding language, and programming (Davenport, 2012). Unlike the traditional quantitative analysts that focused on supporting internal decisions, BDA professionals deal with products and processes for external customers and provide support for generating value-adding products and services (Davenport, 2012). In addition to technical skills, firms require managerial skills to make appropriate strategic decisions based on the new information generated from BD. This means that managers require the ability to generate useful insights based on the extracted information and make decisions on how it will be used to support other business units, customers, and other stakeholders.

Intangible resources do not have definite boundaries, and it is difficult to quantify their values. These resources are generally difficult to trade in the market; however, some intangible
resources, such as copyrights, patents, and trademarks can be traded between organizations (Grant, 2005). Gupta and George (2016) discuss two types of intangible resources that can lead to BDAC: data-driven decision-making culture and intensity of organizational learning. Organizational culture has been raised as one of the reasons for the variance observed in the successful implementation of BDA deployments; it has been argued that culture has a larger influence than technological factors (Lavalle et al., 2011). Firms tend to make important decisions based on experience, market trends, and intuitions of the top executives, which tends to be the highest paid individual’s opinion (McAfee and Brynjolfsson, 2012). A concept of data-driven culture refers to the extent to which the decision-makers of the organization make decisions based on the insights extracted from the data. This means that organizations that follow the traditional decision-making processes, where decisions are significantly influenced by the individual’s title or hierarchy, are less likely to benefit from BDA.

The firm’s efforts toward exploring, storing, sharing, and applying the knowledge related to BDA is related to the intensity of organizational learning (Gupta and George, 2016). Grant (1996) suggests that organizational knowledge generated from the aggregation of individual (Gupta and George, 2016) special knowledge leads to performance improvement, and unlike technologies that may become outdated and replaced, the knowledge does not. This type of resource can be especially important in market conditions with high uncertainties, and organizations with higher intensity of organizational learning are likely to have garnered more BDA-based knowledge. As shown in Figure 1, BDA resources are necessary to develop BDAC, which provides the organization with the ability to analyze and extract information from the
BD gathered. Therefore, BDA resources are viewed as the prerequisites for the development of BDAC for organizations (Gupta and George, 2016).

1.1.3 Big Data Analytics Capability (BDAC)

It has been recognized that the successes of BDA deployments encompass a wider range of facets beyond tangible, human, and intangible resources. Recent studies show that having BDA resources is necessary but not sufficient in generating competitive performance improvements, and that organizations need to effectively manage and allocate these resources (Wamba et al., 2017a; Wang and Hajli, 2017). As a potential explanation to this conundrum, BDAC has been presented, which is the organization’s capacity to handle the large amounts of data and provide insights that can generate value (Garmaki et al., 2016).

Some definitions of BDAC emphasize the processes or practices that are required to leverage BD (Olszak and Zurada, 2020; Yu et al., 2021), while others have focused more on the necessary organizational resources and their arrangements (Dubey and Childe, 2019). The

Figure 1. Classification of big data resources adopted from Gupta and George (2016)
former views BDAC as the organization’s competence to enable other capabilities through BDA (process-view), whereas the latter views BDAC as an information technology-based capability that results from IT tools (resource-view). In general, the existing literature views BDAC as encompassing the related BDA resources to generate performance outcome; however, diverging views and definitions still exist based on the theoretical lens applied (Mikalef et al., 2018). These different views will be further delineated in Chapter 2 of this thesis.

1.1.4 Information, Insights, and Knowledge

Information, insights, and knowledge are related but not interchangeable concepts. If not defined properly, these concepts can cause confusion in understanding the value generation process from BDAC. To bring clarity to the similarities and differences between these concepts, it is sensible to start from data. As Davenport and Prusak (1998) state, data is a set of discrete facts related to events in various formats (e.g., records of written or digital transactions); it can generally be stored in a technology system and serves as an essential component for all organizations. From an OM perspective, data can be viewed as the raw material that goes into producing outputs in the form of information.

The main difference between data and information relates to the notion that information has a meaning and some purpose to the content. It should inform (“to give shape to”) the receiver and contains added meanings from the sender to the receiver. Whether it is considered as value-adding information or simply noise is dependent on both the quality of the sender’s ability to design the information and the receiver’s ability to interpret the information. This nuance is what distinguishes between information and insight, where insights will encompass the intended purpose of the information and shape the receiver’s decisions and actions. Useable information can lead to any decisions that can be acted upon, whereas useful information is used to draw insights that lead to value-added decisions and actions. In OM, the interest in data
analytics has largely been with the different techniques and methods that can be utilized to generate information, and much of the value-added processual changes that resulted from the insights and understanding have been less pronounced (Dutta et al., 2017). Therefore, whether the information can lead to user insights that impact operational value (e.g., improving the process of delivering products or services to its customers) is of importance when considering the values generated from BDAC.

In comparison to the aforementioned concepts, knowledge is comprised of larger breadth and depth, which makes it complex to define. Knowledge is a culmination of context, experience, information, and insights. Knowledge can vary from one individual to another and is dynamic in nature because individuals can learn under different contexts and new experiences. An organization is made up of many individuals with different types and levels of knowledge. Within the organization, knowledge is embedded in the form of both documents or data bases (e.g., patents), and “organizational routines, processes, practices, and norms” (Davenport and Prusak, 1998), which are involved in the organizations’ operational processes. For the purpose of this thesis, knowledge refers to the integration of the knowledge resources and capabilities embedded in the organizational context and routines (Wu and Hu, 2012).

1.2. Healthcare Context

This thesis argues for the significance of contextualized explanations to the phenomenon of BDA deployment gap and treating the context as an “explanatory material” (Welch et al., 2022). Therefore, the context itself plays a critical role in answering the research question. This section reviews the utilization of BDA applications in the improvement or innovation of operational systems in healthcare, current healthcare challenges, potential opportunities of BDA in mitigating the existing healthcare challenges, and current issues and challenges of BDA utilization in healthcare. The objective of this section is to address the suitability of
healthcare as a context in the examination of BDA deployment gap phenomenon and in answering the research question presented in this thesis.

1.2.1 Introduction

Historically, healthcare has lagged in the adoption of BD relative to other industries (Groves et al., 2013). Although at a slower pace, health information technology (IT) has been steadily growing, generating not only large volumes of clinical data but also a variety of different operational and organizational data. The availability of BD in healthcare is growing at a rapid pace and is one of the fastest growing sectors, which is projected to grow at an exponential rate (Kamble et al., 2019). With the growing compliance and regulatory requirements, countries such as the United States and Canada have already started to generate and collect large and complex datasets in the form of EHR that can be shared within healthcare organizations, and this is true for most developed countries in the world (Kamble et al., 2019). According to a survey conducted by CDC (Centers for Disease Control and Prevention), approximately 86% of office-based physicians use EHR systems and 80% use a certified EHR system in the US (Myrick et al., 2019). As healthcare organizations collect and store numerous data in the form of medical records, wait-times, medical imaging, laboratory test results, and various patient outcome details (Khanra et al., 2020), organizations are looking for ways to better manage and leverage these resources for sustainable competitive advantage through BDA. This is evident in the growing number of BDA applications in the healthcare industry (Galetsi and Katsaliaki, 2020; Kamble et al., 2019).

The ability to extract useful information from vast amounts of data can provide insights on creative pathways and avenues of value for healthcare organizations. These potential values of BDA can come in the forms of improved quality of life, preventative medicine, personalized medicine, more efficient disease diagnosis and effective treatments, reduction in LOS (length-
of-stay), and reduction in healthcare costs for patients and hospitals (Grover et al., 2018; Kamble et al., 2019; Raghupathi and Raghupathi, 2014; Wang and Hajli, 2017). However, to effectively capture these benefits, healthcare organizations are faced with several challenges as organizations are required to handle large databases of sensitive personal information and implement practices to effectively leverage the data to generate value. Sivarajah et al. (2017) identify three main categories of BD challenges: 1) data challenges related to the characteristics of the data, 2) technique challenges related to the capturing, storing, integrating, and transforming of the data, and 3) management challenges related to the governance of data, privacy, and security. Along with these technical challenges associated with BD itself, healthcare organizations face process challenges related to the leveraging of BDA to generate business value that exists in healthcare (Wang et al., 2019).

The shift towards digitization of healthcare has propelled the era of BDA to deliver unforeseen opportunities and related challenges for healthcare organizations. To leverage the large amounts of data generated in healthcare, organizations must develop appropriate BDAC to generate useful insights for strategic and operational decision-making. This positions the healthcare context as an appropriate context to examine the leveraging mechanisms of BDAC to generate value. The next section of this chapter briefly reviews the extant literature on current challenges in the healthcare system and the role of BDA in mitigating these challenges.

1.2.2 Challenges in Healthcare OM

The three dimensions of cost, quality, and access have been commonly used in OM to evaluate the performance and functioning of various healthcare systems (KC et al., 2019). Iron Triangle of Health by Kissick (1994) applies these foundational dimensions in OM to assess the performance of healthcare systems in the work-based fulfillment of demands in a timely, productive, and consistent manner. Under this paradigm, each of the dimensions represents
healthcare issues of priority, and any changes in one dimension has a corresponding impact on the other two dimensions (e.g., improvement in cost will lower the quality and accessibility of the healthcare system). On the contrary, the field of OM supports the notion of the complex and dynamic nature of the healthcare systems where improvement of one dimension does not necessarily have to be compensated by deterioration of another.

Provided that healthcare organizations develop technological and organizational innovation capabilities, KC et al. (2019) argue that elements of operational systems (e.g., processes and workflows, people and roles, policies and procedures, information and data, tools, and technologies) can experience improvements without having to trade off cost, access, and quality against each other. An objective of healthcare OM is to produce and manage the workflows, enhance patient care, optimize utilization of resources, and improve the overall efficiency of the operational system to provide the patients with accurate healthcare service needed at the right time with apt quality at an affordable and lowest cost possible. With the integration of BDA, the healthcare industry will likely experience a shift towards more innovative models for care delivery and improvements in the overall day-to-day performance of the healthcare systems.

1.2.2.1 Cost Challenges

Healthcare expenditure in North America has been steadily increasing and ranks amongst the highest in the OECD (Organization for Economic Cooperation and Development) (CIHI, 2019). In 2018, US healthcare costs reached $3.6 trillion, increasing 4.6 percent over the previous year and representing approximately 18 percent of the total GDP (Hartman et al., 2020). At the same time, Canada spent $254.4 billion, increasing 3.9 percent over the previous year and representing approximately 11 percent of the total GDP (CIHI, 2021). The Canadian numbers are expected to have increased to $331 billion since the COVID pandemic (CIHI, 2021).
Canada and the US operate under two different healthcare systems. The US uses a multi-payer system, where a significant portion of costs are privately funded, whereas Canada’s single-payer system has been mostly publicly funded. The majority of the European countries also use the single-payer system, which provides universal healthcare that ensures health insurance for the citizens. The general consensus has been that the single-payer system is superior to the multi-payer system due to the reduced average healthcare spending per individual and insurance that is not contingent on the individual’s income or occupation. However, this conclusion is not entirely true. The effectiveness of the system needs to be examined with a consideration of value for the patients. A single-payer system prioritizes primary care over specialized care and hospitalization compared to the multi-payer system. For example, the average citizen within a single-payer system could be healthier than a citizen of a multi-payer system, but the service quality and patient outcomes for serious illness may not be as high. Patients with acute illnesses may benefit from the single-payer system, whereas patients with chronic illnesses may suffer from it. Therefore, one system should not be viewed as superior to another, but rather as serving different purposes. Healthcare systems are not limited to only the two presented, but most take the form of the single- or multi-payer system with minor variations.

Regardless of the healthcare systems, both share one major issue: high healthcare expenditure relative to other OECD countries where US is estimated to spend $12,318 (USD) per capita and Canada is estimated to spend $5905 (USD) per capita (OECD, 2021). US has the highest healthcare expenditure with Canada ranking 10th highest (OECD, 2021). The potential role of BDA in mitigating the high cost of healthcare can be significant (Raghupathi and Raghupathi, 2014). The estimated savings from BDA is between $350 billion and $410 billion annually by 2025 in US healthcare, where two of the largest areas for potential savings
are in clinical operations and research and development (Singhal and Carlton, 2019). Other avenues for cost reduction in healthcare exist with BDA in the forms of effective care delivery, enhanced clinical productivity, variability and waste reduction, non-clinical efficiency, and consumer-focused sites of care.

1.2.2.2 Quality Challenges

Capacity Issues

In addition to high costs, healthcare systems experience capacity-related issues that impact the quality of care. The capacity issues are expected to continue based on the trends in population ageing, where it is estimated that by 2050, one in six individuals will be over the age of 65 in the world (United Nations, 2019). In 2019, one in eleven (9%) individuals were over the age of 65 and people in this age group outnumbered children under the age of five at a global level for the first time in history (United Nations, 2019). The increase in the number of aging populations in the world is indicative of the expected rise in demand in the healthcare systems because the increased illness is generally correlated with increasing age (Denton, 2013). Along with the high demand in healthcare, there is a trend of insufficient supply of care providers, in particular nurses (Drennan and Ross, 2019), and evidence of overcrowding concerns in the ED (emergency department) due to shortages in supply of hospital beds and caretakers (Schappert and Burt, 2006).

A natural consequence in a mismatch between demand (high) and supply (low), many patients experience longer wait-times and lower service satisfaction from the overall lower quality of care (Anderson et al., 2007). In 2018, the median wait-time at an ER (emergency room) was 22.4 minutes and 3.2 hours for the US and Canada respectively. The delay can lead to lower quality of care and adverse patient outcomes, such as increased rate of readmission or mortality rate (Denton, 2013). With the expected increase in demand and limited capacity in
healthcare services, informed managerial decision-making is paramount for an efficient allocation of healthcare resources.

Decision-making in healthcare is a complex process and is made while taking into consideration the healthcare organizations’ strategic goals and values, in relation to physicians, patients, and multiple stakeholders (e.g., insurance companies, policy makers) with potentially conflicting goals. Relative to the traditional operations and supply chain in manufacturing, a higher degree of uncertainty and variability is involved in healthcare. Variance in the quality of inputs (e.g., illness or condition of the patients) makes it difficult to produce consistent high-quality outputs (e.g., patient outcome). In addition, the significant amount of uncertainty with demand, service time, and what constitutes a ‘good’ healthcare service adds another layer of complexity to the decision-making process in healthcare. BDA can potentially reduce some of the variabilities that exist in the care delivery process through more precise and efficient diagnostics, predictive analytics for demand, and patient monitoring (Singhal and Carlton, 2019), which can lead to improved capacity utilization and resource allocation.

Bottleneck and Patient flow

Healthcare organizations are consistently trying to make the delivery processes more efficient and treatments more effective by improving utilization of existing resources and eliminating waste. This is especially challenging due to the pressure of delivering higher quality patient care while minimizing the cost. During the care delivery process, patients interact with various healthcare professionals (e.g., clinicians, nurses, pharmacists) from various units, which can occur simultaneously, sequentially, or randomly. Due to the constraints related to equipment, hospital beds, available staff, and uncertainty in demand and patient outcomes, it can be difficult to have the appropriate resources required at the right time and place. For example, for a patient that requires cardiovascular surgery within the next three days, the hospital may
not have any OR (operating rooms) available until the next week or may not have a surgeon available to perform the surgery. This can lead to bottlenecks in the system, which can cause delays in treatment and can sometimes lead to adverse patient outcomes or longer LOS (length-of-stay).

Denton (2013) discusses different causes of bottlenecks in a healthcare system: 1) physical capacity and equipment such as lack of available beds, rooms, medical equipment, and other materials to meet the demand, 2) scheduling, where wasted slots or resources occur due to lack of coordination that causes idling of resources that could be utilized, 3) lack of human resources, such as not having the required number or variety of medical personnel to meet the demand, and 4) information asymmetry between various units and agents (e.g., clinicians and nurses), which can lead to redundant or delayed treatments caused by poor communication or availability of key information such as lab test results, images, or consultations from specialists. The consequences of a bottleneck can vary based on the severity of the patient flow disruption; consequences can range from poor patient satisfaction to lower quality of patient outcome and can be as severe as mortality. Therefore, it is important to design a care delivery process that requires an apt number of resources that meets the needs of the patients without diminishing service quality.

There are multiple stages to a typical care delivery process, and BDA can play an important role in various stages of this process to minimize the amount of time the patient spends at a given stage while receiving apt care service. Efficiency of the process can be improved by reducing the demand variability via preventative care and reducing the number of stages in the care delivery process through standardization and automation or through implementation of multi-purpose service centers. Through EHR, care providers can perform
patient briefing and analysis of patient data at the same time or reduce patient travel time from one stage to another through the use of telemedicine.

1.2.2.3 Accessibility

Customized care

Healthcare organizations often face the dilemma of trying to develop standardized processes for the patients to improve efficiency, but at the same time, are required to deliver customized service for the patients. The nature of the care delivery process involves customization where physicians must make decisions in real-time or near real-time to the patient conditions as needed. This makes it difficult to have high standardized processes. However, to improve efficiency of the care delivery process and reach economies of scale, standardization of processes is essential.

BDA can potentially offer both flexibility and standardization of processes without diminishing the care quality through personalized medicine. Current healthcare systems operate mainly via the traditional “one-size-fits-all” model of disease control (Hopp et al., 2018). This model focuses on the disease and the treatment for the disease rather than the patients (Chawla and Davis, 2013). Personalized medicine takes a more targeted approach where the physicians are advised of the medical treatment that would be most appropriate for the individual patient based on the use of predictive analytics from BDA (KC et al., 2019). Level of personalization is not limited to individual patients; it can also occur at a group level (e.g., race, gender), thus, personalized medicine should be viewed as a continuum of the traditional “one-size-fits-all” on each end of the spectrum. BDA and personalized medicine can offer flexibility to the treatment received by the patients, and the data analysis process during the diagnostics stage can be standardized.
Scheduling

Scheduling challenges in healthcare present significant obstacles in providing timely and accessible care for patients. One of the primary challenges is related to appointment scheduling complexities, which involves the matching of patient preferences, accommodation of multiple providers, coordinating with various departments or facilities, and consideration for the availability of specialized equipment or rooms. Managing these complexities while meeting patient needs can be challenging for care providers. In addition to the inherent complexities related to scheduling, possible no-shows and cancellations from the patients can create variability and disrupt the scheduling process, thus, resulting in wasted resources. Addressing these scheduling challenges in healthcare requires a combination of information from multiple sources and collaborative efforts from multiple healthcare providers, which can lead to inefficient use of the valuable hospital resources.

Kamble et al. (2019) highlight the potential role of BDA in mitigating some of the challenges associated with scheduling through the use of predictive analytics. BDA techniques can be applied to accurately predict the no-shows to support the clinicians in developing schedules that account for variabilities. Available data, such as patients’ attendance records and historical records of patient flows in the emergency departments, can be used to smooth the variations of inpatient schedules, which can significantly improve the accessibility of urgent care services (KC et al., 2019). Predictive analytics from BDA can enable healthcare organizations to accurately anticipate the demand of future resources and appropriately match the supply more effectively in real-time or near real-time.

1.2.3 Applications of BDA in Healthcare

This section reviews the various BDA deployments adopted by healthcare organizations in the real world, where examples of BDA applications in healthcare are shown in Table 1.
<table>
<thead>
<tr>
<th>BDA Applications</th>
<th>Purpose</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient predictions</td>
<td>Operational</td>
<td>Patient predictions for improved staffing and other resources. Using large data sets of hospital admissions records, weather, events, and so forth with machine learning to find more accurate algorithms that predict future admission trends (e.g., collaboration between Intel and Assistance Publique-Hôpitaux de Paris)</td>
</tr>
<tr>
<td>Electronic health records (EHR)</td>
<td>Clinical</td>
<td>The most widespread application of big data in healthcare, EHR can trigger warnings and reminders about patient’s medical records such as new lab results or medications. Digital copies of patient medical records can be shared amongst available providers and significantly reduce paperwork (e.g., Kaiser Permanente in the US)</td>
</tr>
<tr>
<td>Real-time alerting</td>
<td>Clinical</td>
<td>Using medical data in real-time to provide healthcare providers (e.g., clinicians and nurses) with helpful information as they make prescriptive decisions. Can utilize devices such as wearables to collect patients’ health data in real-time and store them in a database (e.g., Asthmapolis, which are inhalers with GPS-enabled trackers to track patients with asthma)</td>
</tr>
<tr>
<td>Informed strategic planning</td>
<td>Clinical</td>
<td>For clinical purposes, BDA can be used to get better insights into patient demographics and identify patterns in the treatments and/or illnesses to make strategic plans for the cluster of patients (e.g., University of Florida made use of Google Maps and public health data to prepare heat maps to identify population with chronic diseases)</td>
</tr>
<tr>
<td>Medical image analytics</td>
<td>Clinical</td>
<td>Analyzing big databases of images (e.g., computed tomography (CT) scans, magnetic resonance imaging (MRI), X-ray, etc.) to identify patterns in the pixels and convert them into information that can be used to help with diagnosis. When implemented well, radiologists may no longer need to see the images (e.g., Carestream and how they integrate big data with medical imaging)</td>
</tr>
<tr>
<td>Predictive analytics in healthcare</td>
<td>Clinical</td>
<td>Using predictive analytics to calculate probability of patients’ likelihood of going to the ICU or other predictions related to patient health so that healthcare providers can prepare care plans accordingly (e.g., Optum Labs using EHRs to predict risk of diabetes in patients)</td>
</tr>
<tr>
<td>Improved telemedicine</td>
<td>Clinical</td>
<td>Primarily used for remote patient monitoring, primary consultation, and diagnosis, but can also be used for telesurgery, where doctors can use robots and high-speed real-time data delivery without physically being with the patient. This can be beneficial to reduce/prevent readmissions for patients by providing personalized treatment plans.</td>
</tr>
<tr>
<td>Reducing fraud and improved claim accuracy</td>
<td>Financial</td>
<td>Using BDA to prevent fraud and/or inaccurate claims for insurance, medications, and so forth, which would save costs. This would be applicable for private and publicly funded healthcare systems because hospitals can apply for funding based on performance and needs. BDA along with</td>
</tr>
</tbody>
</table>
Each BDA deployment serves to either improve or innovate the timeliness (accessibility), productivity (cost), or consistency (quality) of the care efforts and outcomes. Operational purpose indicates that the deployments impact the efficiency of the healthcare system and the processes involved, which impacts productivity and/or timeliness of the care efforts. BDA deployments with clinical purposes are intended to impact clinical outcomes such as care quality and patient outcome, and deployments with a financial purpose impact the management of finances. Despite the heterogenous applications of BDA in healthcare, the BDA applications require certain level of BDAC for it to be deployed and used to generate value. Various BDA applications have been implemented in healthcare with different purposes and forms, which demonstrates the increasing role that BDA plays in delivering value to the patients and stakeholders within the healthcare organizations.
1.3 Overarching Research Objective and Question

Given the surge of BDA applications, many organizations are interested in ways to explore and exploit the potential value of BDA. It will be critical to understand the relationship between BDAC and value. For the last decade, there has been a great degree of focus on examining the role of BDA resources and BDAC in the value generation in organizations (Gupta and George, 2016; Singhal and Carlton, 2019; Wang et al., 2019). The extant body of research brings several insights on the relationship between BDAC and value from various perspectives, dominated by the strategic management and information systems literature. This has led to literature mainly viewing BDAC under the lens of organizational-level capabilities or as information technology in its relationship with competitive advantage and, for the most part, has overlooked the enabled capabilities that mediate the relationship at functional-level and floor-level routines.

Often organizations invest in and deploy BDA initiatives for strategic purposes; however, during the deployment phase, organizations must undergo multiple stages (maturation) where BDA assimilates within the various levels of the organization as BDA becomes an integral part of the everyday operations. To develop a more holistic understanding of how BDAC generates value at an organizational level, we need to also examine the enabled functional-level capabilities from BDAC along with the floor-level routines that lead to improved performances from the OM perspectives. As the means to disentangle the complexities that are involved in the leveraging process of BDA, this thesis seeks to understand: 1/ the different mediating organizational capabilities through which BDAC can lead to value, 2/ various forms of BDA leveraging practices, constraints, enablers, and pressures while integrating BDA into the organization, and 3/ how information generated BDAC transforms
into insights and knowledge that can inform decision-making and actions at multiple levels of the organization.

In particular, this thesis focuses on the context of healthcare. As stated by Welch et al. (2022), a social phenomenon “is not possible to explain” without taking into consideration the context and treating it as explanatory constituents rather than simply as descriptive. Thus, we view context as essential to theorizing that provides help in explaining the research findings related to the phenomenon of *BDA deployment gap* in healthcare. These findings can help healthcare organizations cultivate complementary organizational capabilities that can assist in the leveraging of BDAC and appropriately allocate organizational resources and capabilities. In addition, this research can help OM scholars in identifying the mechanisms or work efforts that entail the conversion of information generated from BDA into knowledge and find ways to better manage the knowledge to improve the organization’s operational and clinical outcomes. Hence, the objective of this thesis is to find answers to the following expansive research question:

*How can BDAC be operationally leveraged to address the BDA deployment gap for value generation in healthcare?*

To answer this question, this thesis employs two empirical studies: the first study collects empirical evidence from the literature through an SLR, and the second study seeks to examine real-world practices of BDAC in healthcare through the multiple case study.
Chapter 2

2. Literature Review

To develop a strong foundation for the thesis, this chapter provides a review of the literature dealing with the broader research area related to the BDAC and its relationship to value. Chapter 3 will then conduct a systematic literature review (SLR) to bring a more focused review of research areas in the healthcare context. First, the General Background section of this chapter will discuss the theoretical lenses adopted in explaining the BDAC framework in the thesis. Then, the Theoretical Background section of this chapter will first discuss RBV (resource-based view), DCV (dynamic capabilities view), KBV (knowledge-based view), and KM (knowledge management). These theoretical views will be used to inform discussions of the BDAC to value relationship. Second, BDAC and value will be defined along with how these constructs are operationalized in the healthcare context with reference to the existing literature. Third, this section will address the leveraging mechanisms of BDAC in value generation, including various BDA framework and value generation pathways. Lastly, this chapter will present a review of the current consensus on the existing BDAC framework and present a conceptual framework that can address the possible gap (denoted as the ‘black box’) in the form of indirect effects within the BDAC to value generation pathway in the existing body of research.

The following chapters proceeds in two sequential phases. The initial phase (Chapter 2) consists of an unstructured preliminary perusing of the prevalent literature to identify and define the established constructs related to BDA and value in the general BD research area. The subsequent SLR chapter (Chapter 3) will expand beyond the direct effects of BDAC on organizational performance and value. In the process, this chapter provides a theoretical
framework that will be used to guide the discussions from the findings from the empirical work in latter chapters of this thesis.

2.1 General Background

2.1.1 Big Data Analytics Capability (BDAC)

It has been recognized that the success of BDA deployment encompasses a wider range of characteristics beyond the quality of data, technology, and analytic techniques (Garmaki et al., 2016; Mikalef et al., 2020b). Recent studies show that having BDA resources is necessary but not sufficient in generating competitive performance improvements and elucidate the need to consider the functioning of operational and organizational variables involved in the process (Mikalef et al., 2020a). As a potential explanation to this conundrum, the existing literature offers BDAC (Ansari and Ghasemaghaei, 2023; Garmaki et al., 2016; Wamba et al., 2017a).

OM and information systems management literature provides several definitions of BDAC (Gupta and George, 2016; Mikalef et al., 2018; Srinivasan and Swink, 2018; Wang et al., 2018a). Some definitions of BDAC that have been employed in the existing literature are provided in Table 2.

Table 2. List of definitions of BDAC and theoretical lens adopted in the extant literature

<table>
<thead>
<tr>
<th>Authors</th>
<th>Definition of BDA capability</th>
<th>Theoretical lens</th>
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<tbody>
<tr>
<td>Davenport and Harris (2007)</td>
<td>&quot;The distinctive capability of firms in setting the optimal price, detecting quality problems, deciding the lowest possible level of inventory, or identifying loyal and profitable customers in big data environment&quot;</td>
<td>None</td>
</tr>
<tr>
<td>(LaValle et al., 2011)</td>
<td>&quot;Ability to use big data for decision-making, which is essentially connected with the business strategy&quot;</td>
<td>None</td>
</tr>
<tr>
<td>(Kiron et al., 2014)</td>
<td>&quot;Competence to provide business insights using data management infrastructure (technology) and&quot;</td>
<td>None</td>
</tr>
<tr>
<td>Reference</td>
<td>Description</td>
<td>Framework</td>
</tr>
<tr>
<td>---------------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>-----------------------------------------------</td>
</tr>
<tr>
<td>(Akter et al., 2016)</td>
<td>&quot;Competence to provide business insights using data management infrastructure (technology) and talent (personnel) capability to transform business into a competitive force&quot; (adopted from Kiron et al. 2014)</td>
<td>Resource-based view</td>
</tr>
<tr>
<td>(Garmaki et al., 2016)</td>
<td>&quot;Firm's ability to mobilize and deploy BDA resources effectively, utilize BDA resources, and align BDA planning with firm strategy to gain competitive advantage and enhance firm performance&quot;</td>
<td>Dynamic capabilities view</td>
</tr>
<tr>
<td>(Gupta and George, 2016)</td>
<td>&quot;Firm's ability to assemble, integrate, and deploy its big data-specific resources&quot;</td>
<td>Resource-based view</td>
</tr>
<tr>
<td>(Wamba et al., 2017)</td>
<td>&quot;Competence to provide business insights using data management infrastructure (technology) and talent (personnel) capability to transform business into a competitive force&quot; (adopted from Kiron et al. 2014)</td>
<td>Resource-based view</td>
</tr>
<tr>
<td>(Wang et al., 2018a)</td>
<td>&quot;The ability to acquire, store, process and analyze large amounts of (health) data in various forms, and deliver meaningful information to users that allows them to discover business values and insights in a timely fashion&quot;</td>
<td>Resource-based view</td>
</tr>
<tr>
<td>(Dubey et al., 2019)</td>
<td>&quot;Organizational facility with tools, techniques, and processes that enable the organization to process, visualize, and analyze data, thereby producing insights that enable data-driven operational planning, decision-making and execution&quot;</td>
<td>Dynamic capabilities view, Contingency theory</td>
</tr>
<tr>
<td>(Wang et al., 2019)</td>
<td>&quot;The ability to acquire, store, process, and analyse large amounts of (health) data in various forms, and deliver meaningful information to users that allows them to discover business values and insights in a timely fashion&quot;</td>
<td>Resource-based view</td>
</tr>
<tr>
<td>(Kamble et al., 2019)</td>
<td>&quot;The ability of the (healthcare) organizations to use the available big data resources to achieve organizational performance&quot;</td>
<td>Resource-based view</td>
</tr>
<tr>
<td>(Kamble and Gunasekaran, 2020)</td>
<td>&quot;Collection of data, analytical tools, computer algorithms and techniques to derive meaningful insights, patterns from the collected large data sets&quot;</td>
<td>Resource-based view, Knowledge based view, Dynamic</td>
</tr>
</tbody>
</table>
In general, BDAC is defined as an organization’s ability to effectively deploy BDA resources (e.g., technology, talent) to capture, store, process, and analyze large volumes of disparate data in (near) real-time towards generation of “critical” insights (Srinivasan and Swink, 2018). This definition is largely influenced by the prominent use of RBV in the literature to explain BDAC through its two main facets: resource-picking and capability-building (Barney, 1991; Teece et al., 1997). Based on the viewpoint of RBV, capability-building processes can only occur after the acquisition of proper resources (valuable, rare, inimitable, non-substitutable), where BDA resources are viewed as a necessary constituent that organizations must invest in to develop BDAC. Thus, BDAC encompasses both the resources (e.g., tools and technology) that collect, and store data and the techniques involved in the visualization and analysis of big data (Lavalle et al., 2011; Srinivasan and Swink, 2018). Figure 2 shows the classifications of these BDA resources that can lead to BDAC (Gupta and George, 2016).
Supposition 1. BDAC results from the leveraging of BDA resources.

Some scholars define BDAC with emphasis on the investments of specific resources necessary for BDA (Dubey et al., 2018; Gupta and George, 2016) while others have focused on the processes or practices that are required to leverage big data (Yu et al., 2021). The former views BDAC as an information technology-based capability that results from IT tools, whereas the latter views BDAC as the organization’s competence to enable other capabilities through BDA. In this thesis, BDAC in the context of healthcare is defined as the healthcare organization’s ability to collect, store, process, and analyze large volumes of health data from various sources that enables delivery of meaningful information to end-users, which allows for better informed decision-making for operations and clinical outcomes. A distinction is made between BDAC and processes that leverage the information generated from BDAC to enable other capabilities, which Winter (2003) describes as a collection of routines, where routines consist of highly patterned behaviors or work efforts. Therefore, this thesis is grounded in viewing BDAC as necessary to deliver meaningful information from BDA resources to the end-users.

Supposition 2. BDAC generates BDA resources-enabled usable information outputs.
2.1.2 Value of BDA

Value and competitive advantage have been commonly used in the literature to refer to a measure of performance (Akter et al., 2016b; Gupta and George, 2016; Mikalef et al., 2018; Su et al., 2022). In the BD literature, the concept of value has been recognized as one of the five characteristics of BD (Brinch, 2018) and is often discussed as the outcome variable of BDA in understanding the relationship between BDA and firm performance (Grover et al., 2018). However, firm performance does not necessarily equate to value and can provide limited understanding of what constitutes value because it is often based on the context and stakeholders (Brinch, 2018). For example, what constitutes desired value from BDA in healthcare may differ from supply chain management or sustainability. Therefore, without a specific reference or description of the context, it is difficult to provide an accurate definition or operationalization of value.

As Brinch (2018) states, the concept of value from BDA has been understudied, and there is a limited amount of research in the literature that thoroughly explains the process of value creation and capture from BDA. Sheng et al. (2017) separate the value generation process from BD into three steps: value discovery, value creation, and value realization. This process-oriented approach argues that BD value does not necessarily come solely from the characteristics of BD, but rather from the processes and implementations firms adopt (Sheng et al., 2017). In the process, organizations go through changes in the alignment of resources and develop new capabilities, and the decision-makers can contextualize and experiment with BDA and ultimately execute the insights attained from BDA to make timely decisions to generate value. From a management perspective, value creation strategies require reconfiguration of the existing organizational structures and processes along with BDA. The baseline assumption of value generation from BDA is that the informational outputs from
analytics lead to better insights that can be used for improved decision-making (Sharma et al., 2014).

Better informed decision-making along with improved efficiency in resource utilization and coordination from BDA can lead to strategic business value in the form of functional value (Grover et al., 2018). This form of value is directly related to performance improvements (e.g., operational, financial performance) due to the adoption of BDA and occurs as a result of synergistic (re)configuration of organizational resources and capabilities along with the development of BDAC. In addition to the functional value, Grover et al. (2018) suggest symbolic value as part of strategic business value that can come from BDA. Adoption of BDA can signal a firm’s intention to innovate to the stakeholders, which can lead to an increase in investments from the agents and increased stock prices. For the purpose of this thesis, business value of BDA mainly refers to its functional value, while keeping an open perspective on the possibility of symbolic value.

2.1.3 Conceptualizing BDAC to Value

Although the topic of potential business value from BDA investments has been a popular point of discussion for the last decade in management (Choi et al., 2018; McAfee and Brynjolfsson, 2012), empirical research examining the validity of such claims has been relatively limited, with most of the publications coming in the last five years (Gunasekaran et al., 2017; Mikalef et al., 2018; Wamba et al., 2017a; Wang et al., 2018c; Yu et al., 2021). The main argument is that BDAC can help make sense of the large volumes of data to provide organizations with the ability to reconfigure business strategies in dynamic market conditions, which gives the organization competitive advantage (Grover et al., 2018).

General consensus in the existing field of IT (information technology) business value and IT capability has been that IT enables organizations to generate competitive advantage
through continuous innovation and improvements of products and services (Bharadwaj, 2000). Within the theoretical lens of RBV, the role of IT capability has been firmly established in the literature and supported by empirical evidence on its association with firm performance (Akter et al., 2016b; Bharadwaj, 2000). Under the premise that BDAC is an extension of IT capability, BDAC has been identified as one of the core organizational capabilities that has a positive impact on firm performance (Mikalef et al., 2020b). Similar to the concept of IT capability, the main assumption in understanding BDAC is that while BDA resources can be easily replicated, the ability to reconfigure and orchestrate these resources in ways to generate performance improvements is difficult to replicate.

To date, a large part of the existing empirical research on BDAC has assumed a direct relationship between BDAC and competitive advantage (Figure 3) (Cörte-Real et al., 2020; Ferraris et al., 2019; Gupta and George, 2016).

![Big Data Analytics Capability to Value Relationship](image)

**Figure 3. Direct value generation pathway view of BDAC to value relationship**

However, more recent studies have begun to posit the need to consider the possible indirect effects of BDAC on competitive advantage through various processes involving other organizational capabilities such as dynamic and ordinary capabilities (Mikalef et al., 2020b; Wamba et al., 2017a; Wamba and Akter, 2019). For instance, Cörte-Real et al. (2020) argue that BDAC is a dynamic capability that enhances the organization’s information processing capability for knowledge creation through the exploitation of big data, thus, providing business insights for improved organizational decision-making. Wamba et al. (2017) make similar claims, arguing that BDAC leads to sustainable competitive advantage directly
through the ability to deploy distinctive and valuable BDA resources and capabilities, and indirectly through dynamic capability by better informed decision-making and strategic planning. In comparison, Mikalef et al. (2020) argue that the effect of BDAC on competitive advantage is not direct, but rather fully mediated by dynamic capabilities, which in turn impact the marketing and technological capabilities of the organization. Therefore, the generation of insights is not sufficient to provide competitive performance improvements and requires transformation of other organizational capabilities through BDAC to influence competitive advantage (Figure 4).

While some studies argue that BDAC is a dynamic capability (Córte-Real et al., 2020) or enabler of dynamic capabilities (Mikalef et al., 2021), others have examined the relationship between BDAC and value from a more socio-technological perspective (Günther et al., 2017), where the emphasis is on the value-generating practices from BDA technologies rather than the dynamic capabilities and competitive advantage. For instance, Lehrer et al. (2018) present a theoretical model under the lenses of affordance and materiality that shares insights on mechanisms where BDA technologies afford two different types of innovation: service automation and human material service practices. Dremel and Herterich (2020) take a similar approach, where the authors find four BDA actualization mechanisms–enhancing, constructing, coordinating, and integrating–under three socio-technical levels (structure, actor, and technology). This perspective acknowledges the context in which BDA technologies are deployed and the people that interact with them, the end-users.
Streams of research related to the role of BDAC in generating business value share dissimilarities and multiple perspectives regarding the conceptualization of the relationship between BDAC and value. At the same time, there have been recurring distinctive insights. First, BDAC can impact the competitive performance of an organization by the enhanced capacity to sense opportunities and threats, seize identified opportunities, and transform organizational resources and capabilities based on changing trends in the market at the organizational level. Second, BDA leveraging practices occur at different levels within an organization (e.g., agents, structure, and technology) and involve continuous cross-level interactions that are interconnected. Third, BDAC can be present in different forms depending on the levels within an organization and can have multiple pathways to value. Fourth, BDAC is necessary but not sufficient in generating value from BDA resources and requires a transformation of information into operational insights that lead to value-added work efforts. Fifth, the level of BDAC will likely depend on the degree of maturity related to the acceptance and adoption of BDA by the organization (internal context) and the industry (external context).

2.2 Theoretical Background

2.2.1 Resource-based View (RBV)

The main theoretical underpinning used in the extant BDAC literature has been based on the RBV (resource-based view) and the dynamic capabilities view (Barney, 1991; Helfat and Peteraf, 2003; Teece et al., 1997), which were adopted to identify and examine how organizations use resources and BDAC to generate competitive advantage (Akter et al., 2016b; Dubey and Childe, 2019; Kamble et al., 2019; Wang et al., 2019). Wide applicability of the RBV has made it a prominent theoretical framework used in the OM field, along with
multiple management disciplines, in particular, strategic management and information systems literature (Hitt et al., 2016).

The RBV posits that a firm have a collection of tangible and intangible resources; however, only the resources that are valuable, rare, inimitable, and non-substitutable (VRIN) can result in sustained competitive advantage for the firm (Barney, 1991). Critics have argued that the RBV has limited explanatory strength and considerations for the dynamic nature of the environment and influence of the external environment, and it lacks clarity in delineating between the concepts of resources and capabilities (Leiblein, 2011). As an extension of the RBV, organizational capability has been proposed to help overcome some of these criticisms and offer insights on the nuances.

Helfat and Peteraf (2003) draw a distinction between organizational resource and capability, providing separate definitions for each. A resource is defined as a tangible or intangible “asset or input to production”, where the ownership and control belongs to the organization. Organizational capability refers to the ability to utilize the collection of resources to perform a set of tasks or combination of them to achieve the desired outcomes (Helfat and Peteraf, 2003). Organizational capability has also been described as a subset of resources or processes that facilitates the orchestration of other resources that improve overall productivity (Akter et al., 2016b). Both resources and capabilities are fundamental components to the RBV. Under the RBV, the competency of the organization is impacted by different strategic implementations of the organizational resources to create idiosyncratic organizational capabilities, which can ultimately lead to the desired performance outcomes and competitive advantage.
2.2.2 Dynamic capabilities view (DCV)

Additional theoretical perspectives, in particular DCV, have been used to further supplement the RBV and extend the understanding of how organizational resources can be used to gain sustained competitive advantage in dynamic environments. Through improved capacity to sense and shape opportunities and threats, organizations can appropriately reconfigure necessary organizational resources to seize opportunities and avoid threats to maintain competitive advantage (Teece, 2007). Dynamic capabilities are, naturally, difficult-to-replicate and do not “directly affect output for the firm…but indirectly contribute to the output of the firm through an impact on operational (ordinary) capabilities” (Helfat and Peteraf, 2003, pg. 999). In simple terms, organizations build capability to make changes to other organizational capabilities as needed based on the changing external and internal environments. This orchestration process of transforming resources into capabilities and how these capabilities can be leveraged to generate improved performance unavoidably require managerial decision-making and actions in the form of various work activities.

Dynamic capabilities have been examined in various forms and have shown theoretical implications and empirical evidence that supports a positive relationship with competitive advantage (Mikalef et al., 2020b; Shamim et al., 2019; Su et al., 2014; Teece et al., 1997). Despite the different definitions of dynamic capabilities in the extant literature, a consensus is that it supports a firm’s ability to retain, learn, and transfer knowledge and helps adapt in the changing environments in the form of identifiable practices or routines (Eisenhardt and Martin, 2000). In other words, dynamic capabilities allow for the reconfiguration of ordinary capability and organizational resources, and this can indirectly affect firm performance (Cepeda and Vera, 2007; Helfat and Peteraf, 2003). The transformation process of the firm’s knowledge in the form of strategic decision-making and
development of new products and services can lead to performance improvements in a
dynamic environment (Helfat and Winter, 2011). Therefore, firms with dynamic capability
can change how they “make a living” by supporting specific patterns of activities or routines
with explicit purpose, and this is shown through the patterned behaviors within the
organizations. To further extend this theoretical perspective, the KBV (knowledge-based
view) offers KM (knowledge management) processes as a way organizations develop
routines and knowledge resources through organizational learning (Argote, 1999; Eisenhardt
and Santos, 2012).

2.2.3 Knowledge-based View (KBV) and Knowledge Management (KM)
Organizational learning has been understood as one of the foundations of the KBV. This is
based on the fundamental process of learning by which information is integrated into the
behavior of individuals, creating changes in behaviors, thus, leading to a collection of
patterned behaviors. These collections of patterned behaviors are manifested from the
knowledge resources (e.g., experience, knowledge, routines) of the agents based on the
learning process and can be represented in the form of organizational routines (Argote,
1999). Within the KBV, the concept of resources branches out to include the knowledge-
based resources as part of the intangible assets that can be used to inform and reconfigure
organizational resources and capabilities that lead to competitive advantage over time (Grant,
1996). In the management literature, the KBV is often used to complement both the RBV and
the DCV (Eisenhardt and Santos, 2012).

Based on the broader perspective of the KBV as an extension of the RBV, knowledge
is viewed as a resource that can be used to maintain competitive advantage for organizations.
This process of leveraging knowledge-based resources to improve performance and create
value is referred to as KM (Cepeda and Vera, 2007). Knowledge is the systematic
combination of experience, skills, and expertise of individuals and organizations. KM is operationalized in the form of practices and activities involved in the creation, flow, and use of the knowledge towards value added outcomes (Li et al., 2012). KM has been widely studied and applied in healthcare because the services have substantial dependence on the knowledge of individual experts, and KM can provide ways to enable learning, collaborating, and sharing between professionals to help improve the care delivery process, quality of care, and cost of care (el Morr and Subercaze, 2010; Kothari et al., 2011; Stefanelli, 2004; Wu and Hu, 2012). This perspective can provide explanations as to why knowledge-based resources are important in helping organizations gain superior performance; however, it does not provide helpful explanations regarding how knowledge is used to create value.

Drawing from the DCV literature, Bogner and Bansal (2007) distinguish between having a RBV of knowledge-as-resource in comparison to the process view of knowledge-as-process. The study argues that the knowledge from a process perspective is an outcome in the form of new knowledge through learning, and this new knowledge–from a resource perspective–becomes the key input to enable process capabilities that are rooted in sets of routines and activities that generate value. Similarly, Wu and Hu (2012) use knowledge assets and knowledge capability to draw a line between viewing knowledge-as-resource and knowledge-as-process. Knowledge assets serve as the input resource that goes into the value-creation process and can be present as the organization’s intellectual resources, such as specialized experts, technology, and tools. Knowledge capability is the organization’s ability to make use of these knowledge assets and generally consists of the knowledge acquisition, transfer, integration, and application processes (Bogner and Bansal, 2007; Grover and Davenport, 2001; Turner and Makhija, 2006; Wu and Hu, 2012).
2.3 The ‘Black Box’

The extant capability literature generally divides capability into two categories, either dynamic or ordinary (operational) capability (Cepeda and Vera, 2007; Drnevich and Kriauciuonas, 2011; Helfat and Peteraf, 2003; Helfat and Winter, 2011; Teece et al., 1997). Ordinary capability is how an organization “makes its living” in the day-to-day operations, whereas dynamic capability is what alters, improves, and/or engenders ordinary capability (Drnevich and Kriauciuonas, 2011; Helfat and Winter, 2011). Cepeda and Vera (2007) adopt a KM (knowledge management) view to distinguish between ordinary (zero order) and dynamic (first order) capability using a sequential model. From this perspective, dynamic capability reconfigures the firm’s breadth and depth of knowledge resources and routines through KM processes. The knowledge resources and routines are how a firm “makes its living”, which is defined as the ordinary capability. Thus, dynamic capability can impact the firm’s ordinary capability based on the available KM processes and reconfiguration of the firm’s resources (Cepeda and Vera, 2007). Ordinary capability enables the firm to perform and aptly complete the fundamental functional activities, which encompass the ability to provide the products and services that generate value for the firm. These functional activities can be viewed as bundles of practices or routines that are performed daily and are used to provide the same products and services to the same general range of customers on average (Helfat and Winter, 2011).

Empirical evidence that supports this view can be found in the study conducted by Vanpoucke et al. (2014), which demonstrates that supplier integrative capability (dynamic capability) can lead to improved process flexibility and cost efficiency (operational capabilities) that results in greater operational and financial performance. A combination of sensing, seizing, and transforming activities within dynamic capability can enable the firm to
identify and gather necessary information for risks and opportunities within the supply chain and make continuous (re)configurations of the operational practices and routines (Teece, 2007; Vanpoucke et al., 2014). Similarly, Dobrzykowski et al. (2016) argue that comprehensive lean orientation, which is a dynamic capability, directly impacts patient safety and indirectly impacts financial performance through internal integration. Initiatives and practices intended to improve processes have shown to improve performance in service quality through the enabled changes in the mindset and reshaping of the organizational culture, which contributes to a development of greater standardization of care delivery processes (Dobrzykowski et al., 2016).

While BDAC has been understood as an antecedent to firm performance in the extant literature (Gupta and George, 2016; Wamba et al., 2017a; Wang et al., 2018a), there still exists a lack of agreement on whether BDAC is a direct or indirect precursor to performance (Mikalef et al., 2020b). Although understanding of BDAC continues to evolve, BDAC’s ability to acquire, store, and process data to generate meaningful information should be viewed distinctively to the leveraging of the information generated to enable reconfiguration of organizational resources and ordinary capability (Tabesh et al., 2019). Therefore, to effectively leverage BDAC, firms would require ordinary and/or dynamic capability that can leverage the insights generated from BDAC. Based on the existing literature, this thesis provides a conceptual framework of this mediator termed the ‘black box’ (Figure 5) and examines the operational mechanisms empirically in Chapter 4. Thus, the objective of this thesis is to empirically provide a process-based, contextualized explanation and operationalization of this construct. This thesis specifically focuses on the advancement of empirical insights on the value-creation step in the value-generation pathway, which is highlighted in Figure 5 by the dotted box as the operational black box.
Supposition 3. BDAC enables the opportunity for value creation but does not directly yield value delivery and value capture.

This chapter highlights the increase in interest in BDAC and its relationship to value through a scoping review of the literature. Within the value generation pathway of BDAC, the focus in the literature has been mainly in different analytic techniques and methods that enable organizations to discover value in the form of BDAC and the potential delivery and capture of the value generated from the outputs of BDAC. This largely overlooks the value creation step that occurs within what has been described as the operational black box. In sum, while how to generate useable information from BDAC has been relatively well understood in the extant OM literature, the mechanisms as to how the useable information is converted into useful insights has been understudied. In the following chapters, this thesis seeks to empirically examine the leveraging mechanisms through the SLR, which utilizes the
literature as the sample, and multiple case studies, which use real-world cases as the samples to examine the BDA deployment gap phenomena in the healthcare context.

Conclusion

The paradigm of digital healthcare has created a shift towards the incorporation of BDA. To find ways to take advantage of the continuously growing amount of healthcare data, healthcare organizations are required to develop BDAC. Similarly, research in the field of BD and BDA has been increasing at a rapid rate (Galetsi et al., 2019; Khanra et al., 2020). Section 2 presented the general literature review of the existing literature on the antecedents of BDAC and its relationship to value to examine the role of BDA in the generation of value. As this scoping review illustrates, the BDA resources are required to develop BDAC for organizations, and follows a sequential pathway to competitive advantage. While the general scoping literature review can be helpful in understanding what has been conducted in the existing literature and develop conceptual understandings of the phenomenon, it does not provide sufficient insights related to the leveraging of BDAC specifically in the healthcare context. In addition, the lack of structure and degree of rigor in general literature review could lead to question of whether the BDA deployment gap exists in healthcare, and disregard the significance of the context. The following section seeks to further strengthen these weaknesses by conducting a systematic review of the literature that focuses on the topic of BDAC and value in the context of healthcare to assess the existing research on the mechanisms involved in the leveraging of BDAC.
Chapter 3

3. Systematic Literature Review (SLR)

3.1 Introduction

SLR has been a noteworthy research method in various research fields, offering knowledge generation and refinement and discovering research gaps in the literature (Cook et al., 1997; Khorasani and Cross, 2020; Moher et al., 2009; Wemmerlöv, 2020). The degree of reliability and bias that may exist in the reviews are dependent on the rigor of the review process; a rigorous process includes an appropriate and well-defined research scope along with replicable and transparent review protocols (Cook et al., 1997; Durach and Wieland, 2017; Thomé et al., 2016). Therefore, it is essential to have a detailed outline of each step involved in the review process documented with transparency. In addition to acceptable rigor, the SLR process should consider the ontological and epistemological idiosyncrasies that exist in the research domain (Durach and Wieland, 2017).

Guides providing exemplars to conducting a well-structured SLR in the literature include Thomé et al.’s (2016) recommendation of a seven-step approach (adopted from vom Brocke et al., (2009)), an eight-step guide to conducting a stand-alone SLR by Okoli (2015), six-step SLR guidelines recommended by Durach and Wieland (2017), a three-stage review process by Galetsi et al., (2019) that follows PRISMA (principles of systematic reviews), the three-step process suggested by Khorasani and Cross (2020), and the six-step SLR process adopted by Wemmerlöv (2020). The variations observed between the SLR processes recommended by each author(s) are mainly related to the degree of detail or the specifics of the discipline of research. Thus, using the aforementioned recommended SLR processes as a
reference, this thesis uses a six-step literature review process, primarily adopting the methods recommended by Durach and Wieland (2017) and Wemmerlöv (2020), shown in Figure 6.

3.2 Methodology

This section offers a detailed explanation of the six-steps from Figure 6 to clearly outline the review process conducted in this SLR. The objective of Chapter 3 is to review and build upon the general research question and the conceptual framework developed in the previous chapters by offering a contextualized explanation to the phenomenon of interest, emphasizing the healthcare context. The research questions for the SLR are driven by the general research question from Chapter 1 of the thesis, *how can BDAC be operationally leveraged to address the BDA deployment gap for value generation in healthcare?*

3.2.1 Step 1: Identify the Purpose and Frame the Research Questions

The initial step to the SLR starts with appropriately defining the research question and theoretical framework. Specific research questions have been developed with the objective of understanding the conditions and context in which certain theories work or do not work in
adequately explaining the real-world phenomenon of leveraging BDA for value generation in healthcare. In addition, the objective of this SLR is to identify and seek consensus on the constructs involved in the BDA to value framework, theoretical lenses adopted, and to further extend how the current theoretical frameworks are used to understand the phenomenon. The research questions to be answered in the SLR are:

**RQ 1.** What are the various frameworks in examining BDAC and its relationship to generating value in healthcare?

**RQ 2.** What are the constituents of the mediating construct ('black box') within the relationship between BDAC and value in the context of healthcare?

**RQ 3.** What is the extent of existing literature on BDAC and its relationship with ordinary and dynamic capabilities in the context of healthcare?

### 3.2.2 Step 2: Determine the Inclusion/Exclusion Criteria

The second step was to develop inclusion and/or exclusion criteria, where specific criteria were chosen to determine whether each publication is appropriate in providing the information needed to answer the research questions arrived at in step 1. The inclusion and exclusion criteria and the rationales behind each criterion are shown in Table 3. Carefully constructed inclusion and exclusion criteria were used not only to reduce the raw number of entries in the database but also to choose publications that align with the following aspects of the theoretical framework: context of study, definition and the operationalization of the constructs, and unit of analysis (Durach and Wieland, 2017).

*Table 3. Criteria for including or excluding papers in the systematic literature review*

<table>
<thead>
<tr>
<th>Inclusion criteria</th>
<th>Rationale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Publication in peer-reviewed scholarly journals</td>
<td>Peer-reviewed journals along with conference proceedings tend to be of higher quality than non-peer-reviewed papers</td>
</tr>
</tbody>
</table>
Papers must include BDA, BDAC, dynamic capability, operational capability, and value generation from BDA as the main theme

The focus of the research pertains to the leveraging of BDA to generate value, where BDAC and other forms of capabilities are of interest

Papers must include healthcare as the study context

The research seeks to examine the value generation process and the mechanisms involved in leveraging BDA in healthcare

Papers published from 2012 to 2021

Based on previous literature reviews of big data in OM by Lamba and Singh (2017), there has not been any publications of big data related papers prior to 2012 in OM

Theoretical, empirical studies, and review papers (either qualitative or quantitative papers)

Research area has received contributions from various approaches

<table>
<thead>
<tr>
<th>Exclusion criteria</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Papers that focus primarily on the characteristics of big data OR analytical methods</td>
<td>The objective of the research is not on big data or the specific analytical tools and methods</td>
</tr>
<tr>
<td>All studies or publications in any language other than English</td>
<td>The researchers involved in the review are English language readers</td>
</tr>
<tr>
<td>Editorial comments</td>
<td>Editorial articles and comments did not have sufficient content on its own, hence, they were mainly used as a reference for the papers reviewed</td>
</tr>
</tbody>
</table>

The primary studies were strictly limited to publications in peer-reviewed and scholarly journals. Excluding unpublished studies and conference proceedings can result in the risk of publication bias in the form of dismissing some of the recent studies and the potential bias from the researcher’s tendency to lean towards publishing studies with positive results (Thomé et al., 2016). However, it is a common method to only include published, peer-reviewed, and scholarly journals in an SLR (Khorasani and Cross, 2020; Pilbeam et al., 2012; Wemmerlöv, 2020), and it is postulated that academic work from peer-reviewed journals will be of higher quality with greater rigor, transparency, detail, and less bias relative
to the unpublished studies. Therefore, this SLR confines the searches to articles published in peer-reviewed and scholarly journals (editorial articles and comments were excluded) in English only because the researcher involved in the review process was only able to read and understand English.

Given that the focus of the SLR is on the leveraging of BDAC to generate value in the context of healthcare, primary studies that did not pertain to the topic of organizational level change from BDA, developing of BDAC, and the mediating and/or moderating role of other forms of capabilities, along with business value, were excluded. Based on the literature review of BD in OM by Lamba and Singh (2017), the number of publications of BD-related papers prior to 2012 in OM is very limited, thus, primary studies were selected from 2012 to 2021. Both quantitative and qualitative studies (regardless of the type: theoretical, empirical, or review papers) were included in the study because the research area related to BDA has received contributions from various approaches and it would be difficult to justify choosing one type of study over another.

3.2.3 Step 3: Determine the Search Procedures

Electronic searches were used as a primary tool to find the primary studies for the SLR. Literature sources were from 8 different electronic databases: INFORMS/ABI, EBSCO – Business Source Complete and Academic Search Ultimate, SAGE, Wiley, Emerald Insight – Business Management & Economic Book Series, Taylor & Francis, SCOPUS, and WOS (Web of Science). At least two databases are recommended for an SLR, and broader diversification of primary studies is preferred (Wemmerlöv, 2020). Instead of using a single search engine and retrieving publications through links to other databases, each database was searched one at a time and any duplicated results were removed afterwards.
The searches were restricted to title and/or abstract of the documents instead of searching the full text of documents, mainly for practical reasons. Searching for title and/or abstracts in SLRs is a common practice, and full text searches resulted in too many returns, making it inefficient and impractical to conduct a thorough review (Khorasani and Cross, 2020; Okoli, 2015). In addition, the primary interest is in the value generation process from BDA resources and BDAC, and it is reasonable to assume that if these were a significant contribution of the study, it would be emphasized in the title or abstract of the paper (Wemmerlöv, 2020). For comparison and transparency purposes, the search was conducted in both full text and with just title and/or abstract; however, it was decided to include only the latter for manual qualitative screening due to the reasons discussed.

To adhere to the degree of rigor, transparency, and replicability of the exemplar SLRs in extant literature, a complete and detailed search string for full-text and title and/or abstract searches is in Appendix A. General descriptions of the search settings are as follows:

- **Main topic** – “Big Data or Big Data Analytics” (one option)
- **Searched in** – Title, title + abstract, and full-text (three options)
- **Different capabilities involved in the value generation process** – “Big Data Analytics”, “Capability”, “Dynamic Capability”, “Operational Capability”, and a combination of all the capabilities (four options)
- **On/off filters for healthcare terms** (two options)
- **On/off filters for peer review + articles + scholarly journal + date between 2012 to 2021 + in English** (two options)

The logic behind the search terms was to identify the number of extant studies that examine the relationship between BDA and value (mainly business value) that involved various organizational capabilities. Different capabilities were initially used to separate searches to
present the proportions of each capability because aggregate search results can mask the subtle differences in the composition. The topic of BDA encompasses multiple contexts and disciplines, thus, can result in a vast number of results if the study context is not identified.

As discussed by Okoli (2015), it is important that the search adheres to the research questions and the developed theoretical framework while ensuring that it is not too narrow such that the searches “yield too few studies to be helpful.” Therefore, the SLR incorporates the ‘on’ or ‘off’ filters for the healthcare terminologies and publications in peer-reviewed journals criteria. The ‘off’ setting searches are used as a benchmark to identify the publications without limiting the search to a specific context, and the ‘on’ setting was used to compare the studies in the healthcare context with the benchmark.

3.2.4 Step 4: Select the Pertinent Literature and Create Synthesis Sample

The number of returns from each of the selected searches can be found in Table 4. Adding the healthcare terms to the searches significantly reduced the number of results from 22,349 articles to 15,560 for full-text searches with the terms, and ultimately narrowing it to 60 articles for either title or abstract searches. Of the 60 articles, 15 duplicates were removed.

The remaining articles were then put through a qualitative screening process, where the articles were manually screened to ensure the applicability of the articles for research purposes. At the end of this step, a total of 45 articles remained to be qualitatively screened in more detail.

Table 4. Number of returns from selected searches

<table>
<thead>
<tr>
<th>Search Type (with filters)</th>
<th>BDAC</th>
<th>Dynamic Capability</th>
<th>Operational Capability</th>
<th>Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full-text search without filters and without healthcare terms</td>
<td>1990</td>
<td>13100</td>
<td>21650</td>
<td>42048</td>
</tr>
<tr>
<td>Full-text search without filters but with healthcare terms</td>
<td>1081</td>
<td>7771</td>
<td>16314</td>
<td>30462</td>
</tr>
<tr>
<td>Full-text search with filters and without healthcare terms</td>
<td>1067</td>
<td>8766</td>
<td>16155</td>
<td>22349</td>
</tr>
</tbody>
</table>
The next step involved the initial pruning of the results from the searches. This step consisted of validating that all the results had full-text versions available and removing any duplicates. First, the abstracts of the articles were reviewed and selected based on their relevance to the theoretical framework and research questions. The selected articles were then reviewed in full. During this process, five articles were rejected because the abstracts lacked focus and relevance. Upon further review of the articles, three more articles were rejected due to the inaccessibility of the full text of the articles, where either only part of the articles were translated into English or certain sections of the study were missing. This left a total of 32 articles, which were then coded and analyzed. All of these selected articles focused on:

- The use of BDA in the context of healthcare; and
- Value generation from BDA; and
- Discussion of one or combinations of BDAC, dynamic capability, and ordinary (operational) capability.

3.2.5 Synthesize the Literature

In this step, the synthesis sample was summarized based on descriptive, methodology, and thematic categories for additional analysis (Table 5). To increase efficiency in reviewing the articles, the information was documented and organized in a spreadsheet format. As the topic of BDA in healthcare is multidisciplinary, descriptive information was extracted along with
methodological and thematic information from each of the articles. While description of the entirety of each paper was not written in full detail, thorough examination, detailed reading, screening, and a coding process were performed in accordance with the categories in Table 5.

The main structure of the categories was adopted from Pilbeam et al. (2012), and the sub-categories were chosen carefully by the researchers until a consensus was reached. When consensus could not be reached, inputs from the experts in the fields were requested for further guidance until a logical agreement was reached.

Table 5. Categories and sub-categories used for data extraction and analysis in the systematic literature review

<table>
<thead>
<tr>
<th>Category</th>
<th>Sub-category</th>
<th>Information</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Descriptive</strong></td>
<td>Year</td>
<td>Year of publication</td>
</tr>
<tr>
<td></td>
<td>Journal</td>
<td>Journal of publication for the paper</td>
</tr>
<tr>
<td></td>
<td>Title</td>
<td>Complete title of the paper</td>
</tr>
<tr>
<td><strong>Methodology</strong></td>
<td>Paper type</td>
<td>Analytical: categorized into conceptual, mathematical, or statistical</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Empirical: categorized into case study, experimental design, survey study,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>and mixed methods</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Literature review: categorized into topics</td>
</tr>
<tr>
<td></td>
<td>Theoretical lens</td>
<td>Yes: theory-based research study, which theoretical lens was adopted</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No: does not adopt a theoretical lens (phenomenon-based research study)</td>
</tr>
<tr>
<td><strong>Thematic</strong></td>
<td>Purpose</td>
<td>Objective of the paper</td>
</tr>
<tr>
<td></td>
<td>Context</td>
<td>Context within the healthcare field (e.g., specific disease, hospitals, big</td>
</tr>
<tr>
<td></td>
<td></td>
<td>data analytics projects)</td>
</tr>
<tr>
<td></td>
<td>Type of big data</td>
<td>Health information technology (HIT), electronic health records (EHR),</td>
</tr>
<tr>
<td></td>
<td></td>
<td>biomarkers, quality of life data, neuroimaging data, and healthcare data</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(if not directly specified)</td>
</tr>
<tr>
<td></td>
<td>Definition of big data</td>
<td>3Vs (volume, velocity, and variety)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4Vs (addition of veracity)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5Vs (addition of value)</td>
</tr>
<tr>
<td></td>
<td>Big data analytics framework</td>
<td>Presence or absence of a conceptual or theoretical framework to explain</td>
</tr>
<tr>
<td></td>
<td></td>
<td>the relationship between big data analytics capability and business value</td>
</tr>
<tr>
<td></td>
<td>Types of capabilities</td>
<td>Big data analytics capability, dynamic capability, and operational capability</td>
</tr>
</tbody>
</table>
Mechanisms: Steps and process in how big data analytics transforms big data resources and infrastructure to generate value
Value from big data analytics capability: Information on the realized and potential value of big data analytics (quality - consistency, accessibility - timeliness, and cost - productivity)

3.2.6 Report the Findings and Results

The aggregated summary of the synthesized samples can be found in Table 6, which uses the synthesized categories discussed in section 3.2.6 to further analyze and review the papers accordingly in a concise table format. In the next section, the results of the SLR will be presented, while elaborating on the categories presented in Table 6.
Table 6. Aggregated summary of the reviewed papers based on the synthesized categories

<table>
<thead>
<tr>
<th>Author</th>
<th>Paper Type</th>
<th>Journal Type</th>
<th>Theoretical Lens</th>
<th>Defines Big Data</th>
<th>Framework</th>
<th>Themes</th>
<th>Types of Capabilities</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alrahbi et al. (2020)</td>
<td>Empirical</td>
<td>Mgmt.</td>
<td>ST, OT</td>
<td>No</td>
<td>No</td>
<td>1</td>
<td>○  ●  ○</td>
<td>Quality – Consistency; Cost - Productivity</td>
</tr>
<tr>
<td>Bala &amp; Venkatesh (2017)</td>
<td>Empirical</td>
<td>Mgmt.</td>
<td>StrT</td>
<td>No</td>
<td>Yes</td>
<td>1</td>
<td>●  ○  ○</td>
<td>Cost - Productivity</td>
</tr>
<tr>
<td>Brakenhoff et al. (2018)</td>
<td>Empirical</td>
<td>Medical</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>2</td>
<td>○  ○  ●</td>
<td>Quality - Consistency</td>
</tr>
<tr>
<td>Clegg et al. (2017)</td>
<td>Empirical</td>
<td>Science</td>
<td>STST</td>
<td>No</td>
<td>No</td>
<td>3</td>
<td>○  ●  ○</td>
<td>Quality – Consistency</td>
</tr>
<tr>
<td>Coatney (2018)</td>
<td>Empirical</td>
<td>Medical</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>4</td>
<td>●  ○  ●</td>
<td>Cost – Productivity</td>
</tr>
<tr>
<td>El Naqa et al. (2018)</td>
<td>Lit. Review</td>
<td>Medical</td>
<td>No</td>
<td>No</td>
<td>2,4</td>
<td>○  ○  ●</td>
<td>Quality – Consistency; Cost – Productivity; Accessibility – Timeliness</td>
<td></td>
</tr>
<tr>
<td>Fabian et al. (2015)</td>
<td>Analytical</td>
<td>Mgmt.</td>
<td>Yes</td>
<td>No</td>
<td>6</td>
<td>●  ○  ●</td>
<td>Accessibility – Timeliness</td>
<td></td>
</tr>
<tr>
<td>Goh et al. (2016)</td>
<td>Lit. Review</td>
<td>Mgmt.</td>
<td>CFT, ECDT, MODMT</td>
<td>No</td>
<td>Yes</td>
<td>5</td>
<td>●  ○  ●</td>
<td>Quality – Consistency; Cost – Productivity; Quality – Consistency; Cost – Productivity; Accessibility – Timeliness</td>
</tr>
<tr>
<td>Gupta &amp; Ghosh (2019)</td>
<td>Lit. Review</td>
<td>Mgmt.</td>
<td>No</td>
<td>No</td>
<td>3</td>
<td>○  ○  ●</td>
<td>Cost – Productivity; Accessibility – Timeliness</td>
<td></td>
</tr>
<tr>
<td>Howie et al. (2014)</td>
<td>Lit. Review</td>
<td>Medical</td>
<td>Yes</td>
<td>No</td>
<td>4</td>
<td>○  ○  ●</td>
<td>Cost – Productivity; Accessibility – Timeliness</td>
<td></td>
</tr>
<tr>
<td>Kohn et al. (2021)</td>
<td>Lit. Review</td>
<td>Medical</td>
<td>No</td>
<td>No</td>
<td>1</td>
<td>○  ●  ●</td>
<td>Accessibility – Timeliness</td>
<td></td>
</tr>
<tr>
<td>Liu et al. (2018)</td>
<td>Empirical</td>
<td>Medical</td>
<td>No</td>
<td>No</td>
<td>3</td>
<td>●  ○  ●</td>
<td>Quality – Consistency; Cost – Productivity; Quality – Consistency; Cost – Productivity; Accessibility – Timeliness</td>
<td></td>
</tr>
<tr>
<td>Maggi et al. (2018)</td>
<td>Lit. Review</td>
<td>Medical</td>
<td>No</td>
<td>No</td>
<td>4</td>
<td>●  ○  ●</td>
<td>Cost – Productivity; Accessibility – Timeliness</td>
<td></td>
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<tr>
<td>Nisar et al. (2020)</td>
<td>Empirical</td>
<td>Mgmt.</td>
<td>RBV, DCT</td>
<td>No</td>
<td>Yes</td>
<td>5</td>
<td>○  ●  ○</td>
<td>Accessibility – Timeliness</td>
</tr>
<tr>
<td>Qoronfleh et al. (2020)</td>
<td>Lit. Review</td>
<td>Science</td>
<td>No</td>
<td>No</td>
<td>4</td>
<td>○  ○  ●</td>
<td>Quality – Consistency; Cost – Productivity; Accessibility – Timeliness</td>
<td></td>
</tr>
<tr>
<td>Ratia et al. (2018)</td>
<td>Empirical</td>
<td>Mgmt.</td>
<td>Yes</td>
<td>Yes</td>
<td>5</td>
<td>○  ●  ○</td>
<td>Quality – Consistency; Cost – Productivity; Accessibility – Timeliness</td>
<td></td>
</tr>
<tr>
<td>Reddy &amp; Sharma (2016)</td>
<td>Lit. Review</td>
<td>Mgmt.</td>
<td>EGT</td>
<td>Yes</td>
<td>No</td>
<td>4</td>
<td>○  ○  ●</td>
<td>Accessibility – Timeliness</td>
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<tr>
<td>Authors</td>
<td>Type</td>
<td>Domain</td>
<td>ADO</td>
<td>BD</td>
<td>Quality – Consistency</td>
<td>Cost – Productivity</td>
<td>Context</td>
<td></td>
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<tr>
<td>-------------------------</td>
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</tr>
<tr>
<td>Sarin (2014)</td>
<td>Lit. Review</td>
<td>Medical</td>
<td>Yes</td>
<td>No</td>
<td>4</td>
<td>○</td>
<td>Quality – Consistency</td>
<td></td>
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<tr>
<td>Shatil et al. (2015)</td>
<td>Lit. Review</td>
<td>Medical</td>
<td>No</td>
<td>No</td>
<td>3</td>
<td>●</td>
<td>Cost – Productivity</td>
<td></td>
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<tr>
<td>Shokouhyar et al. (2020)</td>
<td>Empirical</td>
<td>Mgmt.</td>
<td>Yes</td>
<td>Yes</td>
<td>7</td>
<td>●</td>
<td>Quality – Consistency; Cost – Productivity</td>
<td></td>
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<tr>
<td>Spreco et al. (2018)</td>
<td>Empirical</td>
<td>Medical</td>
<td>No</td>
<td>No</td>
<td>2</td>
<td>○</td>
<td>Quality – Consistency; Cost – Productivity</td>
<td></td>
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<tr>
<td>Wang et al. (2018) A</td>
<td>Empirical</td>
<td>Technology</td>
<td>No</td>
<td>Yes</td>
<td>4</td>
<td>●</td>
<td>Quality – Consistency; Cost – Productivity; Accessibility – Timeliness</td>
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<td>Wang et al. (2018) B</td>
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<td>Mgmt.</td>
<td>Yes</td>
<td>Yes</td>
<td>7</td>
<td>●</td>
<td>Quality – Consistency; Cost – Productivity; Accessibility – Timeliness</td>
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<tr>
<td>Wang &amp; Hajli (2017)</td>
<td>Empirical</td>
<td>Mgmt.</td>
<td>Yes</td>
<td>Yes</td>
<td>7</td>
<td>● ○ ○</td>
<td>Quality – Consistency; Cost – Productivity; Accessibility – Timeliness</td>
<td></td>
</tr>
<tr>
<td>Warrington et al. (2015)</td>
<td>Lit. Review</td>
<td>Medical</td>
<td>No</td>
<td>No</td>
<td>4</td>
<td>○ ○ ●</td>
<td>Accessibility – Timeliness</td>
<td></td>
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<tr>
<td>Wehrens et al. (2020)</td>
<td>Empirical</td>
<td>Medical</td>
<td>Yes</td>
<td>No</td>
<td>1</td>
<td>● ○ ●</td>
<td>Quality – Consistency; Cost – Productivity; Accessibility – Timeliness</td>
<td></td>
</tr>
<tr>
<td>Westra &amp; Peterson (2016)</td>
<td>Lit. Review</td>
<td>Medical</td>
<td>Yes</td>
<td>No</td>
<td>4</td>
<td>○ ○ ●</td>
<td>Accessibility – Timeliness</td>
<td></td>
</tr>
<tr>
<td>Yu et al. (2021)</td>
<td>Empirical</td>
<td>Technology</td>
<td>Yes</td>
<td>Yes</td>
<td>7</td>
<td>● ● ○</td>
<td>Accessibility – Timeliness</td>
<td></td>
</tr>
<tr>
<td>Zhan et al. (2020)</td>
<td>Empirical</td>
<td>Medical</td>
<td>No</td>
<td>No</td>
<td>2</td>
<td>○ ○ ●</td>
<td>Quality – Consistency</td>
<td></td>
</tr>
</tbody>
</table>

**Theoretical Lens:** ST (stakeholder theory); OT (organizational theory); StrT (structuration theory); STST (socio-technical systems theory); CFT (classical formal theory); ECDT (empirical-cognitive decision theory); MODMT (multi-objectives decision-making theory); RBV (resource-based view); DCT (dynamic capabilities theory); EGT (endogenous growth theory); CT (contingency theory); ILMV (information lifecycle management view); PBV (practice-based view); KBV (knowledge-based view); IPV (information-processing view); CBV (capability building view); NPT (normalization process theory)

**Context:**
1 – changes in the organizational structure from BDA adoption; 2 – use of BDA for a specific disease treatment and control; 3 – BDA technology; 4 – transformation of routines and practices through BDA implementation; 5 – role of BDA in data driven decision-making; 6 – challenges of healthcare data and information sharing; 7 – developing BDAC.

● – presence of the category (yes). ○ – absence of the category (no).

**Types of capabilities:** BDAC (big data analytics capability), DC (dynamic capability), OC (ordinary capability).
3.3 Results

3.3.1 Studies Over Time and Nature of the Studies

Although the selection criteria placed a restriction on the publication date to articles that were published post 2012, the majority of the papers have been published since 2015 (29) with three papers published prior to 2015 (Howie et al., 2014; Purkayastha and Braa, 2013; Sarin, 2014). Of the 29 papers, more than half of the papers (19) were published since 2018. This trend is in accordance with the observations in the literature review of BD in OM conducted by Lamba and Singh (2017), and a similar outburst of publications on BDA in healthcare literature has been reported by (Galetsi and Katsaliaki, 2020).

Of the 32 papers, approximately two thirds of the articles were empirical (19) and the rest were reviews (12), with one analytical paper. The analytical paper (Fabian et al., 2015) used modelling architecture to address impeding challenges related to security and privacy in the adoption of cloud computing in healthcare. Empirical papers were predominantly divided into either survey (7) or case study (8) based research papers, with a few studies that used experimental designs (Brakenhoff et al., 2018; Liu et al., 2018; Zhan et al., 2020) and a mixed method approach (Wehrens et al., 2020). Survey studies used primary data collected from managers and healthcare employees from various organizations, with one of the studies using secondary survey data from recent studies conducted in the healthcare industry (Coatney, 2018). The case studies used in the reviewed papers were largely from organizations with BD projects in the healthcare context. Both primary (Bala and Venkatesh, 2017; Clegg et al., 2021; Purkayastha and Braa, 2013; Ratia et al., 2018; Spreco et al., 2018; Wang et al., 2019) and secondary case study sources (Wang et al., 2018c, 2018a; Wang and Hajli, 2017) were used.
3.3.2 Theoretical Lens

A near split was observed between papers that adopted some theoretical lens (14) and the ones that did not (18), which were then further divided into research categories based on the type of journals to look for any noticeable patterns (Table 7). The research categories were business management, medical, and technology, and these were determined based on the paper’s journal of publication. A significant number of papers that adopted or referred to some theoretical lens were from management focused journals (10 out of 14), with two papers respectively from technology (Wang et al., 2018a; Yu et al., 2021) and medical or science focused journals (Clegg et al., 2021; Wehrens et al., 2020).

Table 7. Application of theoretical lens for each research stream category

<table>
<thead>
<tr>
<th>Research Stream Category</th>
<th>Management</th>
<th>Technology</th>
<th>Medical/Science</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theoretical Lens</td>
<td>Yes</td>
<td>10</td>
<td>2</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>4</td>
<td>0</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>14</td>
<td>18</td>
</tr>
</tbody>
</table>

Overall, 17 different theoretical lenses were found in the synthesized samples of papers, where the predominant theories were the RBV (Nisar et al., 2020; Wang et al., 2019, 2018c; Wang and Hajli, 2017), the DCV (Nisar et al., 2020; Wang and Hajli, 2017) and IPT (Information Processing Theory) (Wang et al., 2019; Yu et al., 2021). Other theoretical lenses adopted were found no more than once in the papers (e.g., contingency theory was adopted in only 1 of the 14 papers). Of the 18 papers that did not adopt any theoretical lenses, a large portion were from the medical stream (15 out of 18), and three were from the business management stream (Fabian et al., 2015; Gupta and Ghosh, 2019; Ratia et al., 2018). It is common for literature reviews (10 out of 18) to not incorporate any theoretical lens so these numbers should be considered with this in mind. The objective of this SLR is not to evaluate
the appropriateness or richness of a theory for a study or to argue the need for a presence (absence) of a theory in research studies. The category of theoretical lens is intended to provide a general descriptive understanding on the types of research studies and the frameworks deployed in the relevant research papers.

3.3.3 Contextual Themes for BDA in Healthcare

For the purpose of this SLR, the contexts have been purposefully selected and restricted to the healthcare industry because the objective is to observe the extant literature that is specifically related to the leveraging of BDAC in healthcare given the increase in the availability and generation of data in the healthcare context. By examining a specific industry, it is possible to focus on the subtle nuances and ontologies related to the context and avoid the potential drawbacks that can come from covering too many industry sectors. Through a conceptual abstraction, seven categories of contextual themes have been identified:

1. Changes in the organizational structure from BDA adoptions (4)
2. Use of BDA for a specific disease treatment and control (4)
3. BDA technology (4)
4. Transformation of routines and practices through BDA implementations (10)
   a. Precision/personalized medicine and improving quality of care (5/10)
5. Role of BDAC in data-driven decision-making (4)
6. Challenges in healthcare data and information sharing (2)
7. Developing BDAC (5)

Because BDA is such a broad research topic, even within the healthcare context, there were variations in how BDA was investigated based on the focus of the research papers. Using the seven contextual themes identified, the relationship between BDA resources and BDAC with business value is further examined. The seven themes may or may not be unique to the context
of healthcare and do not form an exhaustive list. However, these themes can represent emerging research topics for future research interests and empirical investigation. The contextual themes identified in the SLR will be further empirically advanced through the multiple case study in Chapter 4 of this thesis.

3.3.3.1 Changes in the Organizational Structure from BDA Adoptions

There were three empirical papers and one literature review paper that examined the changes that occur from the adoption of BDA at an organizational level. The changes consist of both the potential benefits and challenges during the adoption process, with greater emphasis on the benefits of BDA. A study conducted by Alrahbi et al. (2020) emphasizes the importance of organizational strategy, orientation, and readiness for BDA in the adoption of HIT (health information technology). In this paper, HIT consists of different integration of BDA techniques. Along with the alignment of organizational strategy and orientation to match with HIT and BDA implementations, managing the reactions and resistance by the employees and stakeholders of the healthcare organizations were shown to be a significant factor to BDA adoptions (Bala and Venkatesh, 2017).

The changes occur as employees develop BDAC and new business processes through the adoption of BDA and the organizations undergo institutionalization and routinization of the new business processes, which can lead to positive economic outcomes and operational efficiency (Bala and Venkatesh, 2017; Kohn et al., 2021; Wehrens et al., 2020). Educating the stakeholders (e.g., managers, clinicians, patients) can play a significant role in enabling organizations to develop the required capabilities to embrace the changes and effectively leverage BDA (Kohn et al., 2021). Both micro and macro aspects of process changes have shown to be impacted by BDA adoption. Unfortunately, there were limited practical implications as to the mechanisms of how healthcare organizations and managers can
effectively reconfigure and leverage organizational resources to better prepare for BDA adoptions and how to transform information into capabilities and knowledge that can be used to generate business value.

3.3.3.2 Use of BDA for a Specific Disease Treatment and Control

In addition to the organizational level examination of BDA and its potential value in improving performance, several studies that examined the impact of specific BDA tools on the treatment and control of specific disease were found. The purpose of these studies is largely to demonstrate the usefulness of BDA and the potential value it can provide in improving patient outcome and overall care quality (Brakenhoff et al., 2018; El Naqa et al., 2018; Spreco et al., 2018; Zhan et al., 2020). These studies demonstrate that BDA tools have shown to provide improved detection and prevention of specific diseases such as influenza and asthma (Spreco et al., 2018; Zhan et al., 2020). A literature review conducted by El Naqa et al. (2018) assesses the potential value that can come from increased availability of BD and various analytic techniques in the field of oncology, in particular, with more effective clinical decision support systems that can provide ways to individualize cancer treatments and make quicker changes to the treatment regimens. In addition to the benefits, Brakenhoff et al. (2018) warn of the potential danger of measurement errors with the use of secondary BD (e.g., routine care data), and this can lead to under- or overestimation of exposure to outcome relationship. All the papers reviewed were in the medical stream, where performance or impact of BDA for specific disease treatment and control were of principal interest.

3.3.3.3 BDA Technology

Although the technological aspect of BD has been widely studied, it is generally limited to the introduction of the analytic tools that use BD and the performance of the tools under some controlled conditions. Shatil et al. (2015) review the cloud computing technology and provide
an overview of the benefits and barriers of the technology itself in handling large datasets such as medical imaging (e.g., neuroimaging) and other healthcare data. The cloud computing technology can be challenging for end-users (e.g., clinicians) and can lead to privacy and security concerns; therefore, practical overviews and background knowledge are required for this type of technology to be leveraged in healthcare. Similarly, Gupta and Ghosh (2019) review the impact of 5G technology on the future of healthcare in transforming healthcare practices, with descriptions of different applications that use BDA in healthcare. There have also been empirical studies that explore and evaluate the performance of specific BDA technologies and systems in the healthcare context (Clegg et al., 2021; Liu et al., 2018). Empirical evidence show that well incorporated BDA systems can provide increased flexibility and efficiency in the daily operations by providing access to medical information in real-time across multiple network platforms.

3.3.3.4 Transformation of Routines and Practices Through BDA Implementations

Routines and ordinary capabilities with organizational learning have shown to play a significant role in improving efficient and effective processes in organizations (Levitt and James G. March, 1988; Wu et al., 2010). With the increase in healthcare organizations incorporating electronic forms for record systems and other healthcare informatics, organizations experience transformations in the current best practices and routines in the healthcare system. A blend of empirical study and literature review papers have shown that the development of BDAC in healthcare organizations leads to a transformation of a bundle of practices through the use of BDA (Coatney, 2018; Howie et al., 2014; Maggi et al., 2019; Qoronfleh et al., 2020; Reddy and Sharma, 2016; Wang et al., 2018c). The BDA-enabled transformations in healthcare organizations can provide insights on various possibilities for value generation from BDA. Commonly discussed BDA implementation started with the
introduction of EHR (electronic health records) or EMR (electronic medical records), where the healthcare organizations can make informed decisions based on the informational outputs generated from the patient records (Wang et al., 2018c). This can lead to improved care coordination and operational flexibility.

Precision and personalized medicine appeared frequently in the articles, with the notion of transformation in healthcare practices from BDAC, where five out of ten papers (El Naqa et al., 2018; Howie et al., 2014; Maggi et al., 2019; Qoronfleh et al., 2020; Reddy and Sharma, 2016) discussed the potential of customized healthcare services for patients from leveraging BDA. All of the papers consider the possibility and the potential benefits of personalized medicine, although, mostly conceptual and indicating the direction that the healthcare system should be moving towards in the future. Real-time generation and analysis of large volumes of healthcare data along with the integration of EHR can help in developing necessary organizational capabilities to provide customized treatments, create disease risk profiles, and design management plans for each patient. This can result in improved flexibility in the daily operations of care practices, service quality, and reduction in healthcare costs (Maggi et al., 2019). However, a limited amount of empirical evidence to which the context of personalized medicine is applied in current healthcare practices was present, and the majority of the studies only reviewed the potential role of BDAC in the impending transformation in the healthcare system.

3.3.3.5 Role of BDAC in Data-Driven Decision-making

The potential benefits of decisions that are based on data and the corresponding improvement of the decision-making processes have been a topic of interest for both scholars and practitioners in healthcare (Belle et al., 2015; Kamble et al., 2019). Healthcare organizations can utilize BDAC to support the ability to make better informed decisions for various end-
users (e.g., clinicians, management, insurance companies) by implementing decision support systems and developing decision-making capabilities to take the information generated from analytics to further support the frontline and backend decision-makers.

Both empirical (3) and review (1) papers examined the role of BDAC in decision-making processes and capabilities (Goh et al., 2016; Nisar et al., 2020; Ratia et al., 2018; Wang et al., 2018a). Decision-making has been viewed as a driver or dimension of BDA value, and the ability to make data-driven decisions is dependent on the healthcare organization’s ability to take information from BDA resources and effectively transform that data into useful knowledge and decisions that can generate value. Nisar et al., (2020) show that the leadership focus of the organization on BD, BD talent management, technology, and organizational culture towards BD are antecedents to decision-making capabilities, which, in turn, impact the organization’s decision-making quality. Empirical support for the impact of BDA on decision-making can be found in the study conducted by Wang et al. (2018a), which shows that the effective use of BDA tools can indirectly impact decision-making effectiveness through absorptive capacity (Cohen and Levinthal, 1990).

3.3.3.6 Challenges in Healthcare Data and Information Sharing

An often-discussed challenge related to BDA pertains to information sharing between and within organizations, and this issue is exacerbated in the context of healthcare due to the complex nature of healthcare and high degrees of silos, which add variability that hinders the ability to coordinate, communicate, and ensure privacy and security of patient information (Ross et al., 2014; Sarkar, 2017). Although these are of major concern in the implementation of BDA in healthcare, the extent of studies pertaining to the challenges related to data and information sharing in healthcare has shown to be limited relative to its counterpart. Fabian et al. (2015) present a cloud computing architecture that can offer healthcare organizations with
inter-organizational data sharing with encryptions for security and privacy for patient data. Similarly, the paper argues that the use of cloud computing services can work to provide more efficient ways to manage and share large volumes of data to better utilize resources. However, the studies have generally been limited to the information sharing service offerings.

3.3.3.7 Developing BDAC

Organizations can generate value from BDA resources by developing the necessary BDAC (Kamble and Gunasekaran, 2020; Mikalef et al., 2018). The five papers with this theme are all empirical studies and examine the role of BDAC in its relationship to outcome variables. The studies argue that (1) BDA resources leads to BDAC, and (2) the resulting BDAC can lead to generation of value in some form for organizations in the healthcare industry (Shokouhyar et al., 2020; Wang et al., 2019, 2018c; Wang and Hajli, 2017; Yu et al., 2021).

Yu et al. (2021) demonstrate that hospitals in China with BDAC improved their operational flexibility by enabling various departments and functions within the hospitals through improved integrative processes such as real-time information sharing, cross-functional coordination, and collaboration with different members of the organization. Similarly, Wang et al. (2019) demonstrate that BDAC impacts the care quality in ways such as lower average excess readmissions ratio and improved patient satisfaction through the interactions with organizational resources and capabilities. In addition to the indirect effects of BDAC on value, empirical evidence of direct relationships with value is demonstrated by improving supply chain sustainability in healthcare organizations (Shokouhyar et al., 2020), where dimensions of BDAC included BDA infrastructure flexibility and the ability of the BDA units to handle routines in a standardized format and manage related resources. BDAC impacts on the value generation from BDA include improvements in operational processes, organizational configuration, process standardization, and managerial decision-making (Wang and Hajli,
Highest number of path-to-value chains started with data processing component to analytical capability, which resulted in operational benefits, followed by the data visualization component of BDA to faster decision-making capability that resulted in operational benefits.

Different dimensions of BDAC resulted in multiple benefits with business value, and these benefits can be attained through multiple pathways. In addition, all of the examined literature indicates a non-recursive path to describe how organizations develop BDAC. As previously suggested in Figure 1 of the thesis, the findings from the SLR support the notion that developing BDAC occurs linearly from BDA resources and is not iterative in nature.

3.3.4 Definitions and Types of BD

The majority of the practitioners and scholars have emphasized the “three Vs” as the distinguishing characteristics that define BD: volume, variety, and velocity (McAfee and Brynjolfsson, 2012; Raghupathi and Raghupathi, 2014). More than half of the papers (19 out of 32) did not provide any specific definition of BD, while some papers did offer some explicit definitions of BD. The most frequently used definition was the “three Vs” (10), and a few papers also included veracity or data quality (Sarin, 2014) and value (Shokouhyar et al., 2020; Westra and Peterson, 2016) as extensions of the definition. Veracity refers to the reliability and authenticity of BD, and this was particularly important in the context of examining quality-of-life data, which is often self-reported by the patients (Sarin, 2014). Value is the benefits that can be attained from BDA, and it generally comes from the insights that can be gained from BDA. Different forms of value were discussed in the papers, but the most prominent form of value came as clinical and operational benefits.

Various types of BD were identified in the papers. The data type refers to the healthcare data inputs that were analyzed to generate some form of informational outputs. The dominant type of BD discussed was EHR, where more than half of the papers (19) discussed the
important role of EHR in providing organizations with healthcare data to be used for analysis. Along with EHR, biomarkers (5), medical imaging (3), administrative data (1), quality-of-life (1), supply chain management (1), and self-reported data (1) were outlined. In the literature, the term healthcare data referred to compilation of the aforementioned set of data.

3.3.5 BDAC Frameworks

12 out of 32 papers incorporated a BDAC framework that supports a positive relationship between BDAC and value in the context of healthcare, where the majority of these papers were empirical studies (11), apart from one literature review paper by Goh et al. (2016), which uses a “five rights concept” framework for the planning and implementation of decision support systems to develop BDAC (the paper states that it is a survey but does not employ a survey method). The 11 empirical papers provide various frameworks for examining the relationship between BDAC and performance or value, where BDA resources were understood as the antecedents of BDAC (Bala and Venkatesh, 2017; Shokouhyar et al., 2020; Wang et al., 2019, 2018c, 2018a; Wang and Byrd, 2017; Wang and Hajli, 2017; Yu et al., 2021).

All the frameworks posit a positive relationship between BDAC and value, where the focus is largely on the direct value generation pathways. Adopting the frameworks, the empirical papers examine different outcome variables (e.g., decision-making, patient outcome, clinical performance, utilization of resources, process improvement, and operational flexibility) to show the supporting evidence for the positive associations between multiple dimensions of BDAC and different forms of value. The conceptual development of the connection between BDAC and value was similar in 6 of the 11 empirical papers (Wang et al., 2019, 2018c, 2018a; Wang and Byrd, 2017; Wang and Hajli, 2017; Yu et al., 2021), which is likely due to a common presence of a single author for five of the papers, which may have heavily driven the advancement of research in this area. A large part of the conceptual development of the
frameworks was guided by four research papers (Cao and Lumineau, 2015; Lavalle et al., 2011; Ward et al., 2014; Wixom et al., 2013) along with a prevalent theoretical perspective of RBV (Barney, 1991) and DCV (Teece et al., 1997).

3.3.6 Definitions and Dimensions of BDAC

Nearly half of the articles (16) reviewed from the synthesized samples mention or discuss BDAC of some form. This indicates a general consensus regarding the significance of BDAC as a construct. Although the importance of BDAC for generating value from BDA is clearly highlighted, there is a lack of conformity regarding the dimensions of BDAC. This may be attributed to analytic capability literature still being nascent (Srinivasan and Swink, 2018) and the confusion that may arise from distinguishing BDAC and regular data analytics capability.

It is important to make a clear distinction between the dimensions and definitions of BDAC, where dimensions represent the measures of BDAC, and definition is the explanation of the construct. Studies look at BDAC both empirically and conceptually to identify its dimensions, such as BD knowledge exchange, BD collaboration, process integration, models of care, unstructured data, decision support, predictive capability, traceability, auditing capability, clinical decision support capability, data collecting capability, interoperability, data storage capability, quality of the BD resource, BD decision-making quality, BDA infrastructure flexibility, BDA management capability, and BDA personnel expertise capability (Coatney, 2018; Fabian et al., 2015; Goh et al., 2016; Liu et al., 2018; Maggi et al., 2019; Shatil et al., 2015; Shokouhyar et al., 2020; Wang et al., 2018c, 2018a; Yu et al., 2021). Some studies use multiple secondary case studies to show that these elements of BDAC can result in IT infrastructure and operational benefits for healthcare organizations (Wang et al., 2018c, 2018a). Yu et al. (2021) adopt the measures of analytic capability from Srinivasan and Swink’s (2018) work, where the authors state that “analytic capability is a new construct in the literature, hence,
we developed the measures by operationalizing analytic capability as a firm’s use of analytic techniques, as well as the ability to gain insights based on available information that may help with the decision-making process” (pg. 1856). Similarly, Shokouhyar et al. (2020) employ structural equation modelling (SEM) to measure the relationship between BDAC and supply chain sustainability, where empirical evidence is provided that supports a positive relationship between the two constructs. In this study, the BDAC construct is a third-order latent construct with BDA infrastructure flexibility (connectivity, compatibility, and modularity) and BDA management capability (coordination and control) as the second-order latent constructs.

A total of five studies provide a specific definition of BDAC and offer possible explanations for the construct. (Shokouhyar et al., 2020; Wang et al., 2019, 2018a; Wang and Hajli, 2017; Yu et al., 2021). These five studies have adopted definitions from several definitions of BDAC that had already been established in the literature outside of the healthcare context (Akter et al., 2016b; Kamble et al., 2019; Lavalle et al., 2011). A general consensus was observed in the definition of BDAC in the context of healthcare, and the most common definition came from Wang and Hajli (2017, pg. 290), where BDAC is defined as “the ability to acquire, store, process, and analyze large amounts of health data in various forms, and deliver meaningful information to users that allows them to discover business value and insights in a timely fashion.” Under this perspective, the information that is generated from BDA resources enables the users to generate value, in particular, at the level of the end-users.

3.3.7 Dynamic and Ordinary Capability in Relation to BDAC

The literature reviewed in the SLR frequently discusses dynamic and ordinary capability with BDAC as the antecedent to organizational performance and value. A mix of review, conceptual, and empirical papers often refer to the bundle of these capabilities as an organizational development that follows after the implementation of BDA resources and infrastructure. These
developmental changes enable the healthcare organizations to find ways to leverage the BDA deployments. Alrahbi et al. (2020) state that improved knowledge management capability is one of the possible benefits that can come from adopting health information technology (HIT), which can help healthcare organizations overcome the three barriers (technical barriers, readiness to big data and internet of things, and organizational orientation) to a successful adoption. In this study, the authors argue that organizations require the appropriate infrastructural and organizational competency for BD prior to the value creation from BDA. An empirical study conducted by Nisar et al. (2020) examines BD-enabled decision-making capabilities of both private and public hospitals, where this capability is referred to as a dynamic capability. The findings of this paper support the notion that BDA resources are significant antecedents to BD decision-making capability, and that BD decision-making capability improves decision-making quality to improve environmental performance for both types of hospitals. An organization’s absorptive capacity has also been shown to mediate the relationship between business analytics (BA) related technologies in healthcare and decision-making effectiveness (Wang and Byrd, 2017). In the study conducted by Wang and Byrd (2017), effective use of the three tools from BA technologies (data aggregation tools, data analysis tools, and data interpretation tools) is mediated by the absorptive capacity of the organization, which in turn improves decision-making effectiveness. The effects of the BA-related technologies are dependent on the organization’s ability to “identify, absorb, transform, and exploit” the information generated from BA (Wang and Byrd, 2017), which indicates that it is an important dynamic capability that directly impacts the decision-making effectiveness of the organization.

In healthcare, standardized routines are described as regular patterns of activities that healthcare service providers perform during the patient care process (e.g., patient information
transfer, perioperative routines, and rounding) (Goh et al., 2011). These are commonly referred to as hospital routines, which are consistently refined to ensure that the acceptable standard of quality and best practice is followed, which has been emphasized in the literature to impact performance outcomes in hospitals (Goh et al., 2011; Peng et al., 2008). From the capability perspective, these hospital routines can be understood as ordinary capabilities. Half of the reviewed papers (17 out of 32) discuss the transformation that occurs in hospital routines from BDA implementations and the potential benefits that can come from the changes (e.g., daily routines of healthcare professionals, follow-up rotations, medical image analysis, clinical reporting). Empirical evidence supports that the elements of BDAC are linked to the transformation of practices, which results in operational benefits (Wang et al., 2018c). BDA-enabled transformation in practices, such as the use of EHR and data-driven medicine practice, have been shown to lead to business value through a path analysis (Wang et al., 2018c). The business value is attained through the new insights generated from healthcare data along with data-supported outcomes for more reliable care practices for patients. BDAC was also shown to be an enabling antecedent to intra- and inter-organizational collaboration and integration processes for hospitals, which resulted in enhanced information processing capacity for achieving operational flexibility in care delivery (Yu et al., 2021).

As shown in Table 6, of the studies that discuss BDAC, the focus is on either ordinary or dynamic capability, but not both. This indicates that the extant literature denotes that BDAC leads to one or the other (either ordinary or dynamic capability) in healthcare, and the literature does not necessarily investigate BDAC while linking it to both ordinary and dynamic capability together. Based on the findings from this SLR, BDAC is likely related to both dynamic and ordinary capability simultaneously because it provides the organization with the ability to better sense new opportunities, seize the opportunity through swift reorchestration of the
current organizational resources and capabilities, and continuously transform the practices (e.g., the way healthcare organizations deliver care) to integrate BDAC into the organization. Therefore, an evident gap exists in the extant literature that examines all three capabilities together to offer a holistic understanding of the leveraging mechanisms of BDAC in the value generation process.

3.3.8 Operationalization of Value

A large variance can be observed in both the conceptual and operationalization of the construct value in the papers reviewed. There were 14 different dimensions of value and performance improvements. Economic value (11) was most frequently discussed, followed by patient outcome (6), quality of healthcare service (6), operational flexibility (6), decision-making (5), operational efficiency (3), optimization of resources (3), organizational effectiveness (3), organizational efficiency (2), quality of life (2), disease prevention (2), risk mitigation (2), knowledge generation (2), and supply chain sustainability (1). Of the 12 studies that discuss positive economic value of BDA, no study operationalized and measured economic value or cost reduction quantitatively. While the potential cost savings of BDA in healthcare is alluded to in all 12 studies, it was through the cost savings or reductions from the transformation in healthcare practices such as preventative and predictive analytics (Reddy and Sharma, 2016), effective utilization of resources leading to improved cost efficiency (Ratia et al., 2018), and the potential cost savings from the time saved in end-user workflows (Goh et al., 2016).

While most values are not operationalized and empirically measured, a few outcome variables, such as hospital operational flexibility, quality of healthcare service, and decision-making quality, are measured. Yu et al. (2021) measured using criteria such as types of treatments offered (product and service flexibility), variety of available treatment for the patients (mix flexibility), and whether the hospital can offer efficient rescheduling of
appointments to patients (delivery flexibility). Care quality was operationalized through measuring the average excess readmission ratio and total performance score for patient satisfaction (Wang et al., 2019). Decision-making quality was measured by adopting decision-making effectiveness and efficiency items (Nisar et al., 2020), and a study conducted by Wang and Byrd (2017) used and adopted the measurements for decision-making effectiveness from relevant literatures to appropriately fit the healthcare context (Cao and Lumineau, 2015; Lavalle et al., 2011; Wixom et al., 2013).

3.4 Discussion

This chapter systematically reviews the extant literature on the relationship between BDAC and value, in particular, how BDAC is used to generate value in healthcare. Adopting the recommendations from Pilbeam et al. (2012) and Wemmerlöv (2020), the SLR identifies and categorizes a series of different contextual themes, theoretical frameworks, relationships, and constructs in a systematic process. The following section provides a discussion of the findings from the SLR, which is used to generate extended understanding of the BDA deployment gap phenomenon in healthcare and the possible leveraging mechanisms involved in generating value from BDAC by healthcare organizations. The findings from the SLR will be the impetus of and will be further expanded through an empirical examination of the real world in Chapter 4 of the thesis.
3.4.1 Conceptual Framework

As the research area related to BDAC and value in healthcare is relatively nascent, an exploratory approach was taken during the qualitative review process to observe the frequency and interactions of the BDAC frameworks suggested in the synthesized sample of literature. The theoretical perspectives from the initial literature review from Chapter 2 is combined with the findings from the SLR in the context of healthcare to elaborate on the initial conceptual framework introduced in Chapter 2 (Figure 4) and presents a more comprehensive conceptual framework of BDAC to value in healthcare in Figure 7 (RQ 1). At the core of the suggested framework, BDAC does not generate information outputs that directly lead to value, but rather it is viewed as a capability that provides organizations with BDA-based informational inputs, which in turn must be operationally leveraged to generate value. The word operational denotes the work efforts performed by the healthcare organizations in the form of bundles of activities or routines involved in the care delivery process. Therefore, the BDA-based information inputs
provide organizations with the ability to (1) reorchestrate existing resources and capabilities and/or (2) develop new capabilities that result in changes to the routines that deliver the value.

The delivery of the value does not occur based on BDA, but it is enabled by it. In other words, the informational input from BDAC is the result of BDA (BDA-based informational inputs), and the ability to function to achieve some operational outcomes is made possible by BDA (BDA-enabled functioning ability). These BDA-enabled abilities to function are the constituents involved in the leveraging of BDAC in the ‘black box’ (RQ 2), and the subsequent process of reorchestration of resources and capabilities will likely involve the interaction between BDAC, dynamic capability, and ordinary capability (RQ 3). Then, the resulting routines and activities at the functional level are the work efforts that lead to operational outcomes in the form of improved or innovative service offerings, which ultimately leads to value capture in the form of care quality, patient outcome, and cost reduction. This does not change the significance of BDAC in the value generation pathway because the operational outcomes depend on BDA-enabled ability to function; these are the results of the BDA-based informational inputs from BDAC.

3.4.2 BDAC in Healthcare
To develop BDAC, the organization must invest in and acquire appropriate BDA resources (tangible, intangible, and human resources) to develop infrastructure that aligns with the strategic goals (Gupta and George, 2016). The existing literature draws a clear picture regarding the role of BDAC as an important precursor to performance improvement and value generation for healthcare organizations (Choi et al., 2018; Hopp et al., 2018; Wang and Hajli, 2017). However, whether BDAC is enough to generate value and how BDAC leads to value in healthcare is still unclear. Based on the review of the extant literature, this thesis posits that BDAC is necessary but not sufficient in the generation of value for organizations. Wang and
Hajli (2017, pg. 290) define BDAC as “the ability to acquire, store, process and analyze large amounts of healthcare data in various forms, and deliver meaningful information to users, which allows them to discover business values and insights in a timely fashion.” In accordance with this definition, this thesis posits that BDAC does not directly leverage the information. Instead, BDAC is the ability to examine a large variety of data to 1) reveal hidden patterns and associations and 2) generate information that can help organizations make better decisions to discover business value.

**Proposition 1.** *BDA resources provide healthcare organizations with BDA infrastructure to develop BDAC, which is used to generate information through analytics.*

Proposition 1 is offered in this thesis to acknowledge that for healthcare organizations to develop BDAC, BDA resources are necessary. However, the different types of BDA resources that are required will not be examined any further in the empirical study conducted in the next chapter because the research focus of this study is in the leveraging mechanisms of BDAC, not the link between BDA resources and BDAC. There is sufficient existing literature that has examined this relationship and provides a sufficient understanding related to BDA resources.

The notion that BDAC generates information inputs to be leveraged raises the question of *what* is responsible for transforming the useable information into useful insights, and *how* this process occurs. Two types of capabilities are discussed along with BDAC as plausible explanations of mechanisms that leverage what is generated from BDAC (Goh et al., 2011; Wang and Byrd, 2017) and likely involved in the BDA value creation process. Healthcare organizations can interpret and make sense of the information generated from BDAC to make better informed decisions (e.g., strategic, or operational decision-making). Hospital routines can also be refined and transformed through the use of BDA tools that can enable the care providers to design more efficient care processes for the patients.
**Proposition 2.** **BDAC serves to generate information input to be operationally leveraged via ordinary or dynamic capabilities enabled by BDAC to generate performance improvement and ultimately business value.**

Although some empirical validities to proposition 2 can be found in the literature (Wang et al., 2018c; Wang and Byrd, 2017; Yu et al., 2021), ordinary and dynamic capabilities have mainly been studied separately when looking at BDAC, as seen in Table 6. There have been a limited number of empirical studies that examine in depth how healthcare organizations operationally leverage BDAC. In addition, the empirical studies largely focus on the direct implications of BDAC on business value, which fails to offer a more nuanced understanding of what happens during the enabling of various practices and routines that exist within the healthcare organizations through BDAC. To properly explain the workings of ordinary and dynamic capabilities in the relationship between BDAC and value in healthcare, a process-based contextualized consideration is required (Welch et al., 2022).

### 3.4.3 Leveraging BDAC in Healthcare

As previously discussed, BDAC enables organizations to make informed decisions for both operational and strategic goals, and it is one of the main ways that BDA is used to generate value. For BDA to help organizations make informed decisions, it must go through four important phases (Tabesh et al., 2019). During the first phase, the data is converted into insights through analytic processes, where healthcare organizations extract information into aggregated reports from the large volumes of healthcare data. During this phase, BDAC plays a critical role because it involves the ability to acquire, store, process, and analyze large amounts of data in various forms (Wang et al., 2019).

In phase two, the technical findings and insights generated from BD are communicated to the decision-makers. These findings are then transformed into decisions at the individual
and organizational levels. Each decision-maker is required to contextualize the insights and have the acumen to make strategic decisions that align with the overall objective or value. Meanings are attached to the insights and in the third phase, the decisions are transformed into actions in the form of practices and bundles of activities for new service offerings or modifications to the existing care packages.

The resources and capabilities are reorchestrated to successfully execute the decisions, and the existing routines are revised (slightly or significantly) to leverage the insights generated from BDAC (Coatney, 2018). These modified work efforts may improve the process of care delivery, resulting in the generation of value for the healthcare organization. Therefore, the organization’s capability to manage and develop BDA-enabled functioning processes in the form of work activities and routines can lead to value. The final phase involves an iterative process where new data points generated from the modifications are brought back into the large pools of warehoused data and back into the cycle to be analyzed. These new data points can serve as internal sources of data.

**Proposition 3. As healthcare organizations develop BDAC, the care practices go through transformations, which enables the information outputs from BDAC to be embedded into the organizational structure in the form of routines and knowledge.**

3.4.4 Value of BDAC in Healthcare

The value of BDAC is often discussed but has been understudied. A dissonance can be observed in the extant literature regarding the current understanding of what exactly constitutes value from BDAC, and this depends significantly on the context and research perspective. From the perspective of the management literature, a large part of the research focuses on the strategic value and competitive advantage at an organizational level, whereas the OM literature focuses more on the operations systems that create and deliver the products and services.
Within the operations system, BDAC involves a process or set of activities that transform the inputs into value added outputs; hence, a large part of OM literature focuses on managing the various value generating processes (Jacobs and Chase, 2014).

In healthcare, value “should always be defined around the customer” (Porter, 2010, pg. 2477) and is measured by the outcomes achieved relative to the cost instead of volumes of services delivered. Therefore, measures such as financial performance or competitive advantage may not be the most suitable to quantify the realization of value in the context of healthcare. As discussed by Porter (2010), process measurements are important measures of value but are not substitutes for measuring healthcare outcomes because improved processes do not always equate to better healthcare outcomes. However, there are two reasons why it would be important to consider the processes and outcomes related to examining value from BDAC in healthcare. First, both the service providers (e.g., clinicians and nurses) and the end-users (e.g., patients) can realize value from BDAC. A more flexible personalized care delivery process can provide services that better fit the individual characteristics and medical conditions of the patients. In the process, service providers can benefit from the improved care delivery process in the form of reduction in time spent with each patient and better-informed decision-making. Accordingly, the patients can receive treatment that may result in greater outcome per cost. Thus, BDAC can generate impact on both the servicing efforts from the provider and the actual services that the patients receive.

The second reason to examine processes and outcomes is related to the leveraging mechanisms of BDAC. To understand the process of how value is generated from BDAC for different stakeholders in healthcare organizations, it is important to examine the processes involved in the leveraging of BDAC along with the outcomes. Value in healthcare exists in the form of both servicing activities and services (e.g., care package), which are often related. The
literature has mainly focused on performance outcomes from work efforts and offers limited understanding on the enabled transformation of the servicing efforts and services from BDAC. Therefore, to understand the value generation pathway of BDAC in healthcare, further empirical examination of care practices and processes that are enabled from BDAC is required.

3.4.5 Theoretical Implications

Based on the descriptive summaries of the review, there were two main clusters of papers: theoretical-based research and phenomenon-based research (Krogh et al., 2012; Schwarz and Stensaker, 2014). Theoretical-based research is oriented towards a theory and is highlighted by an importation of theoretical guidance and driven by theory. These papers aim to contribute through the refinement, advancement, and enhancement of theory. The second cluster of papers are categorized as phenomenon-based research, where the focus is more on contributing knowledge within certain fields through identifying and conceptualizing the phenomenon of interest (Schwarz and Stensaker, 2014). In these papers, the main underpinning of the research is based on the phenomenon, where the research problems were derived and motivated by the phenomenon of interest.

The first cluster of the papers exhibited a high propensity toward business management papers, whereas the majority of the papers from the medical journals were driven mostly by the phenomenon of BDA implementations and their impact on healthcare, rather than theory. The tendency for business management research articles to be theoretically guided has been common in the literature due to the overwhelming mandate from the field (Schwarz and Stensaker, 2014). In a way, theory has been regarded as an assumed baseline requirement for a good article in the field of business management and OM (Krogh et al., 2012).

When considering a theory, a researcher needs to determine the appropriateness of the theory and whether the theory is sufficient in explaining the phenomenon, relevant causal
relationships associated with the phenomenon, and the contextual idiosyncrasies that may exist. As the phenomenon of leveraging BDA implementations in healthcare is relatively recent, there has not been sufficient time for appropriate theorizing to take place. When trying to understand a phenomenon, preliminary stages of research focus on the generation of insights through exploratory work, and the subsequent studies are then motivated by the data and results obtained from the initial research. Further percolation of the observations propels theorizing, where the researcher can discern the extent to which an existing theory can be applicable in understanding the phenomenon or deviates from it. Numerous theoretical lenses (13) are adopted to explain the implementation of BDA in healthcare. The variance in the theoretical lenses adopted suggests that the current understanding of the phenomenon is still limited.

The main difference between theory-based and phenomenon-based research is that the former starts the research design with a theory-driven problem and relies on the existing theory to solve the problem. The latter does not necessarily have to begin with a theory but can be based on real-world phenomenon of interest to derive the research questions (Schwarz and Stensaker, 2014). Therefore, phenomenon-based research can integrate and advance theory and should not be misconstrued as atheoretical. Although the two different research approaches may appear to be on the opposite ends of the spectrum, this is likely a misrepresentation. The aim is to avoid trying to obsessively fit the problems into theories, while maintaining the refinement and advancement of theory. Stank et al. (2017) offer the notion of middle-ranged theorizing as a way to find the middle ground where theory and phenomenon intersect. Middle-ranged theory seeks to “predict phenomena by focusing on the specific mechanisms that produce outcomes within a particular context” (Stank et al., 2017, pg. 7). This is a suitable approach in trying to understand the BDA deployments in healthcare (the phenomena) by
focusing on the leveraging mechanisms of BDAC in generating value (specific mechanisms that produce outcomes) in the context of healthcare (within a particular context).

Conclusion

The paradigm of digital healthcare has created a shift towards the incorporation of BDA. To find ways to take advantage of the continuously growing amount of healthcare data, healthcare organizations are required to develop BDAC. Similarly, research in the field of BD and BDA has been increasing at a rapid rate (Galetsi et al., 2019; Khanra et al., 2020). While the extant literature emphasizes the potential values of BDA and its positive correlations to performance improvement and benefits, there is a lack of empirical research that examines the mechanisms involved in the leveraging of BDAC in generating value in OM.

This chapter contributes to the overall thesis in three different ways. First, the SLR effectively highlights and summarizes the extant literature on leveraging of BDAC to generate value in the healthcare context. It demonstrates that the direct value generation pathway is likely not sufficient in explaining the leveraging of BDAC, and a deeper understanding of the mediated (indirect) value generation pathway is required. This means that BDAC generates BDA-based information inputs that need to be operationally leveraged. Second, based on the review of the BDAC to value frameworks suggested from the existing literature in the context of healthcare, this chapter offers a revised conceptual framework shown in Figure 7 (RQ 1). The proposed framework identifies, explores, and articulates the plausible constructs and mechanisms (RQ 2) involved in the leveraging of BDAC in the context of healthcare, in particular, highlighting the need to examine the ‘black box’ that operationally leverages the information from BDAC through ordinary and dynamic capabilities (RQ 3). Lastly, it posits the suitability of middle-ranged theorizing in better understanding the phenomena of BDA in healthcare from a process-based view. It is important to treat context as explanatory, rather than
descriptive, thus, the healthcare context adds explanatory value in understanding the overall phenomenon. In sum, this chapter builds on the initial literature review by providing a contextualized understanding to supplement the initial propositions in Chapter 2.

The next chapter in this thesis includes the development and presentation of an empirical study that will be used to test the conceptual framework proposed in Chapter 3. The study will examine how healthcare organizations leverage BDAC to generate value and investigate the reorchestration of the organizational resources and capabilities (e.g., ordinary, dynamic, or both) that may come from the BDA-enabled ability to function. Chapter 4 will introduce a qualitative research methodology that will be used for the empirical study, followed by the multiple case study.
Chapter 4

4. Multiple Case Study

4.1 Why A Qualitative Method?

Qualitative research allows for an examination of numerous phenomena and can be useful in addressing different types of research questions under various contexts (Köhler et al., 2022). In addition, it can help with theorizing and exploring phenomena or context that is little-known and can co-create new understanding through learning and sense-making (Köhler et al., 2022). As the phenomenon of interest, the adoption of BDA deployments and the relationship between BDAC and value in healthcare, is relatively recent, the research in this area remains largely exploratory in nature. This is evident based on the numbers of empirical papers that used qualitative research methods such as case studies (8 out of 19) from the SLR in section 3.3. For example, previous case studies in the SLR examined how healthcare organizations can develop BDAC and identify the potential benefits that can be attained from BDAC (Wang and Hajli, 2017). A significant portion of the empirical papers that adopted qualitative methods such as multiple case study used secondary sources of cases, thus, there is still a need for more qualitative inquiry that uses primary sources of data. In addition, appropriate theorizing appears to be lacking, which can be seen by the diverse applications of theoretical lenses from the results of the SLR.

The digitization of healthcare records has provided healthcare organizations numerous possibilities to create value through the use of BDA. Yet, these organizations continue to struggle to generate value from the BDA investments and BDAC despite the efforts. When trying to understand a phenomenon, the preliminary stage of research generates insights through exploratory work, and the subsequent studies are then motivated by the data and results obtained from the initial research through a combination of identification and sensemaking of
the observations. Research has made significant advancements in understanding the characteristics of BD and the recent phenomenon of BDA, especially the adoption of BDA by organizations in various industries such as healthcare. However, little is known about the plausible drivers or reasons behind the BDA deployment gap phenomenon and why organizations with BDAC are still struggling to generate value, even though the majority of the extant literature on BDA is suggesting that it should lead to surmounting potential values (Belle et al., 2015; Hopp et al., 2018; Raghupathi and Raghupathi, 2014; Wang et al., 2018a). As suggested by Von Krogh (2018), the use of phenomenon-based theorizing is highly suitable for the use of BDA and related technologies in organizations, and the use of BDA in healthcare services has received little attention in OM. For similar reasons, Spring et al. (2022) engage in qualitative research methods to examine IT adoption in the form of AI in the professional service context (law and accountancy firms).

Second, the context and the characteristics of the organizations that will be observed in this research, healthcare organizations that have deployed BDA initiatives, limit the accessibility to meaningful quantitative datasets that can be used for statistical analysis. Healthcare organizations have a strong tendency to withhold the majority of the organizational data within the boundaries of each organization. It is common to see siloed information systems and aversion towards sharing or providing datasets that contain sensitive information related to the healthcare organization unless it is required for disclosure to the public. Even if healthcare organizations were willing to share the datasets, many organizations have yet to start collecting data to measure BDAC, performance indicators, or other capability measures due to the lack of directionality and understanding of these variables.

Lastly, to understand the leveraging of BDA, it is important to consider the context and contingencies related to the environment in which the BDA is being leveraged (Mikalef et al.,
One of the significant characteristics of healthcare OM is the inherent high complexity and variability in the system that involves interactions between multiple agents, departments, and information (Dobrzykowski et al., 2014). Qualitative research has demonstrated benefits in better understanding the relationships between different constructs in highly complex environments (Gummesson, 2006). As healthcare organizations are looking to leverage BDA, the environment is arguably becoming more complex with the introduction of new technology and is likely to disrupt the already chaotic environment. To adequately examine this level of complexity would require a data collection method that is more flexible and adaptive. This makes a qualitative method more appropriate for this research in comparison to quantitative analysis because it allows for adaptability to emerging themes and flexibility to unexpected findings in the process.

4.1.1 Understanding Multiple Case Study

Case study allows for the researcher to systematically examine a real-life phenomenon in-depth without losing its environmental context. Generally, in OM, case research can be categorized into three different methodological approaches based on the significance of general theory and empirical context: theory generation, theory testing, and theory elaboration (Ketokivi and Choi, 2014). Following the case research tree proposed by Ketokivi and Choi (2014), this research calls for a design that is a mix of theory testing and elaboration, with greater emphasis on the latter. This research uses existing theories (e.g., RBV, DCV, and KBV) that can be applied to formulate the research question, and for part of the conceptual framework, these general theories can provide a priori theoretical hypotheses. The RBV and DCV can be used sufficiently to hypothesize the development of BDAC from BDA resources. However, the leveraging of BDAC in the context of healthcare has limited existing understanding to derive appropriate hypotheses. In this case, the research requires an exploration of the empirical
context with more “latitude and serendipity” (Ketokivi and Choi, 2014, pg. 236). The objective of this case research is to contextualize the current understandings from the general theories to test (development of BDAC) and elaborate the theory to adequately explain the leveraging process of BDAC in healthcare.

Unlike the traditional ways of separating theory building as inductive versus deductive reasoning, this research offers a step back from the dichotomy and emphasizes an abductive reasoning to theory building through theory testing and elaboration. An abductive reasoning process values flexibility of the research design and process and can often lead to new perspectives of the phenomenon (Dubois and Gadde, 2002). Compared to an inductive reasoning process to theory building that emphasizes the importance of not starting with a particular theory during observation and eventually leading to theory generation, the abductive process accentuates the importance of initial theoretical insights as a starting point of the research. This research considers multiple theoretical lenses to understand the boundaries of the existing explanations for a relationship or phenomena and widens the perspectives to the investigation (Cassell et al., 2018). The objective is to stay flexible without losing the rigor and replicability of the case study research. The findings and insights from the case studies are presented later in this chapter.

4.2 Introduction

Chapter 4 begins with a re-conceptualization of the relationship between BDAC to value based on the findings and analysis from the previous chapters in this thesis. Upon establishing the theoretical underpinning, this chapter presents a detailed description of the methodology used in this study, including replication approach, case selection criteria, sources of data, pilot studies, data collection procedures, and the coding procedures for the analysis. Subsequently, the findings and insights from the case studies are presented adopting the process-based
contextualization (Welch et al., 2022) to demonstrate the leveraging mechanisms involved in transforming information from BDAC to value in healthcare. This study addresses the following research questions related to the propositions suggested in Chapter 3:

**RQ 1.** *How do healthcare organizations use BDAC to enable the functional-level changes in the care delivery process?*

**RQ 2.** *What operational capabilities are associated with the leveraging of BDAC?*

These two research questions aim to address how BDAC can be effectively utilized to make changes on the work floor and impact the care delivery process and to identify the type of operational (e.g., related to the work efforts) capabilities that are involved in the leveraging mechanisms.

### 4.2.1 Re-conceptualizing BDAC to Value

From a phenomenological standpoint, going from usable BDA-based information to useful insight-based decisions and actions entails the enabling processes that are integrated into the work activities throughout various levels of the organization. It is significant to note that the extant literature largely examines BDAC at an institutional level (Wamba and Akter, 2019; Wang et al., 2018a). This is suitable in strategic management, where the research interests have been with the “higher-level” or firm-level capabilities. However, this approach largely disregards the transformation of the operational processes and the related work efforts (e.g., routine functioning and work activities) that are enabled from BDAC. In OM, the focus is on these important processes and workflows that are often overlooked in the pursuit of grander abstract insights. To better understand the processes that are enabled by BDAC, this study adopts a “work-based view” of OM (Browning, 2020), and examines at a more granular level unit of observation from a theoretical standpoint that focuses on the management of work efforts at a functional level during the BDA deployments to extend the understanding of the
“flow of actions and interactions required to transform valuable (BDA-based) inputs into more valuable (BDA-enabled) outputs” (Browning, 2020, pg. 496) in the context of healthcare OM. As more healthcare organizations look to find ways toward more successful BDA deployments (Singh et al., 2021), there is a growing urgent need to examine the enabling processes and the embedded workflows, which govern the transformation of information into knowledge that leads to value added work efforts.

Based on the broader perspective of the RBV, knowledge is viewed as a resource that can be used to maintain competitive advantage for organizations, and the process of leveraging knowledge to create value is referred to as knowledge management (KM). Knowledge is the systematic combinations of experience, skills, and expertise of individuals and organizations, and KM is operationalized in the form of practices and activities involved in the creation, flow, and use of the knowledge towards value-added outcomes (Li et al., 2012). KM has been widely studied and applied in healthcare because the services have substantial dependence on the knowledge of individual experts, and KM can provide ways to enable learning, collaboration, and sharing between professionals to help improve the care delivery process, quality of care, and profitability (el Morr and Subercaze, 2010; Kothari et al., 2011; Stefanelli, 2004; Wu and Hu, 2012).

The knowledge-as-resource view may explain why knowledge is important in helping organizations gain superior performance, but it does not provide helpful explanations regarding how knowledge is used to create value. Drawing from the dynamic capability view, Bogner and Bansal (2007) distinguish between the knowledge-as-resource view in comparison to the process view, which is described as a knowledge-as-process view. The authors suggest that knowledge from a process perspective is an outcome in the form of new knowledge through learning, and this new knowledge then becomes a key input to the enabled process capabilities
that are rooted in a set of routines and servicing activities that generate value. Therefore, knowledge should be examined with both perspectives in mind. Similarly, Wu and Hu (2012) use knowledge assets and knowledge capability to draw a line between viewing knowledge-as-resource and knowledge-as-process (Grant, 1991). Knowledge assets serve as the input (resource) that goes into the value-creation process and can be present as the organization’s intellectual assets in healthcare, such as human resources with specialized expertise, medical technology, and BDA tools. Knowledge capability is the organization’s ability to make use of the knowledge assets and generally consists of the knowledge acquisition, transfer, integration, and application processes (Bogner and Bansal, 2007; Grover and Davenport, 2001; Turner and Makhija, 2006; Wu and Hu, 2012).

For the last decade, researchers have focused on studying the role of BDA resources and their impact on BDAC (Gupta and George, 2016; Singhal and Carlton, 2019; Wang et al., 2019), which mainly occurs during the knowledge acquisition process (knowledge creation from internal and external sources). This study seeks to extend our understanding towards the knowledge transfer and integration processes, in particular, the operational mechanisms and the transformation of work efforts involved in leveraging the information generated from the BDA applications and BDAC in healthcare organizations. The intention of this thesis is not to disregard the importance of the knowledge acquisition process for organizations, but to examine how the knowledge percolates and amalgamates into changing the organization’s form and function through the interaction between structures (e.g., facilities, norms, and routines) and agents (e.g., physicians, nurses, data specialists) in the healthcare organizations. If healthcare professional service operations (PSO) “create and sell their production capacity by organizing professional service providers who have abstract expert knowledge and can skillfully apply it in complex cases requiring customization” (Dobrzykowski et al., 2016, pg.
then it is of theoretical and managerial importance to examine how the information inputs from BDAC transform into knowledge that is enacted in the form of workflows and routines in the care delivery process. Healthcare professionals are required to constantly maintain and apply the large pool of expert knowledge in the daily workflows under extreme environments characterized by high patient interaction, customization, service process variations, and external pressures (Dobrzykowski et al., 2016). BDAC is expected to improve the servicing efforts under such conditions; however, the conditions and mechanisms of how BDAC actually improves the work efforts at the functional level have been understudied.

The extant body of research brings several insights to the relationship between BDAC and value from various perspectives (Ansari and Ghasemaghaei, 2023; Ferraris et al., 2019; Mikalef et al., 2020b; Wang et al., 2018a), where the majority of the research is dominated by the strategic management and information systems management perspectives. The literature mainly views BDAC under the lens of organizational-level capabilities or as technology adoption in its relationships with competitive advantage. For the most part, it overlooks the enabled capabilities at the functional level and the floor-level routines.

Often organizations invest and deploy BDA initiatives for strategic purposes; however, during the deployment phases, the organizations must undergo multiple stages where BDA assimilates within various levels of the organization as it becomes an integral part of the everyday operations. This can also be referred to as the maturation period. Thus, to understand the relationship between BDAC and value at an organizational level, it is necessary to examine the enabled functional level capabilities from BDAC along with the shop-level routines that lead to improved performance that generates value from an OM view. As the means to disentangle the complexities involved in the leveraging process of BDAC, we examine the other capabilities (e.g., dynamic and ordinary capability) using a multilayer capabilities
framework (Csiki et al., 2023) as a way to understand the enabled functional-level capabilities from BDAC, and the changes that occur in operational practices within the healthcare organizations.

4.3 Methodology

4.3.1 Data Collection and Research Designs

This study adopts a multiple case design that follows a replication logic of treating each case as an experiment (Eisenhardt, 1989; Yin, 1994). The cases were collected using purposeful sampling (Coyne, 1997; M. Patton, 1990) rather than theoretical sampling because we did not have a set theory that we tried to observe prior to conducting the research. Various types of purposeful sampling are discussed by Patton (1990), and we chose to adopt the operational construct sampling method, where we sample for the purpose of studying real-world examples of the constructs of interest (e.g., BDAC and the enabled capabilities). In addition, we applied a criterion sampling technique because the selection of the cases was based on whether the case met the criteria set in place. To be specific, we were looking for healthcare organizations that have a minimum of one to three BDA deployments, are located in Canada, have top management support for BDA adoption (demonstrating strategic alignment with the use of BDA), and have developed the ability to collect, store, process, and analyze large amounts of healthcare data (BDAC).

The process of data collection, coding, and analyses happened concurrently (Patton, 1990). Initial stages of the study are best described as an abductive approach (Gehman et al., 2018), where we formed the preliminary theorization of the phenomenon based on the literature and our subjective views on healthcare organizations and the BDA deployment gaps guided by discussions with healthcare professionals. The objective of this study is theory elaboration. Considering the iterative nature of theory elaboration in qualitative research (Ketokivi and
Choi, 2014), we constantly transition from theory to data, and vice-versa. As data were collected and analyzed, it was not uncommon to find new concepts that generated insights. If we were not familiar with the concepts, then we would search the literature to examine whether relevant theories exist that can further develop and contribute to understanding the phenomenon. Thus, both induction and deduction exist in this iterative process, where we are constantly seeking to connect the empirical world (real-world data) with the theoretical ideas from the literature. In this sense, the philosophical underpinning of the methodology adopted in our study is not positivism nor interpretivism, but critical realism (Gehman et al., 2018). Although in this chapter, the data collection and analysis process are presented sequentially for the purpose of clear presentation of information, we make the effort to stress that it was through a continuous and iterative process (Langley, 1999; Yin, 2018).

Literal replication logic would be applicable for between groups of cases (Yin, 1994) to draw meaningful comparisons as the individual cases were selected so that they predict similar results. We adopt from Yin’s, (2018) replication approach to the multiple case study, which is illustrated in Figure 8. The initial step consisted of developing the preliminary theorization regarding the phenomenon of BDA deployment gap, which was followed by the selection of the cases based on the sampling strategies discussed previously. In conjunction, we worked on designing the data collection protocols (e.g., semi-structured interview protocols, email template, research statement, and ethics). The healthcare organizations were initially contacted through a mix of cold emails and personal contacts from members of the research group. Unfortunately, the timing of this study coincided with the beginning of the COVID-19 pandemic, which made it extremely difficult to obtain responses from the healthcare organizations. In addition, the healthcare organizations that agreed to participate in the research already had to place non-urgent projects on hold to reallocate hospital resources towards the
efforts to combat the pandemic. This resulted in delays from the respondents; however, we were able to maintain the relationship with the healthcare organizations and reconnected as the pandemic restrictions lifted. A large portion of the initial connection occurred via emails and online meetings to build trust.

Figure 8. Replication approach to the multiple case study

Convergent evidence is sought from each case to inform the findings and conclusions for the multiple case study. The dotted-lines in Figure 8 represent a very important part of the multiple case study procedure, the feedback loop. If an important discovery or insights were generated during the study of one of the individual cases, we returned to the initial preliminary theorizations to make appropriate changes to the model or propositions. For example, when a new construct or topic of interest was discovered during one of the interviews, we made appropriate changes to the semi-structured interview protocols to ask the relevant questions.
This redesigning took place prior to proceeding further with any of the data collection and analysis phases. This was done to reduce the risk of disregarding the discoveries made during the multiple case study and avoid being too fixated on adhering to the original research design, which may lead to concerns regarding selective reporting of the data to support the predetermined theorizations. We underscore the importance of having an open outlook toward accepting new discoveries to remain flexible and allowing the data gathering efforts to occur in an emergent fashion while maintaining a certain level of structure in the research design (Gehman et al., 2018; Langley, 1999). Thus, the objective of the data collection plan standpoint was to be consistent and reliable but stay nimble in our data collecting efforts.

The unit of analysis for this study is at the phenomenon level, the BDA deployment gap, and the units of observation are the BDA deployments or initiatives at the functional level of the healthcare organizations. Thorough examination was conducted to ensure that these healthcare organizations displayed significant interest and are actively adopting healthcare data analytics, big data analytics, and other forms of advanced analytics to generate value. We used a combination of methods to examine the status of the healthcare organizations’ BDA deployments; the first was to research the publicly available resources (e.g., website, organization values and goals, news articles) to confirm that the organization demonstrates interest in digitization of healthcare service, use of BDA and technology. This was further supplemented with qualitative data from individuals from healthcare organizations during the pilot study and personal contacts, where we inquired about leading healthcare organizations in Canada related to digitization of health records and BDA deployments. Based on the information gathered, we chose four healthcare organizations that meet the criteria based on our sampling strategy.
All the healthcare organizations are well-established research hospitals located in Canada with a tripartite mandate of clinical care, training of healthcare workers, and research (Table 8).

Table 8. Characteristics of the healthcare organizations in the multiple case study based on number of beds, medical staffs, and hospital characteristics

<table>
<thead>
<tr>
<th>Case</th>
<th>Informants</th>
<th># Of Inpatient Beds</th>
<th># Of Medical Staffs</th>
<th>Hospital Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>HO (A)</td>
<td>8</td>
<td>1100</td>
<td>8800</td>
<td>Tripartite</td>
</tr>
<tr>
<td>HO (B)</td>
<td>4</td>
<td>1000</td>
<td>3750</td>
<td>Tripartite</td>
</tr>
<tr>
<td>HO (C)</td>
<td>3</td>
<td>170</td>
<td>1000</td>
<td>Tripartite</td>
</tr>
<tr>
<td>HO (D)</td>
<td>7</td>
<td>880</td>
<td>5900</td>
<td>Tripartite</td>
</tr>
</tbody>
</table>

* HO = healthcare organization

The healthcare organizations vary in size from a smaller organization to larger healthcare organizations, including one of the largest hospitals in the country. The informants were contacted through a combination of emails and a personal network of professionals working in the healthcare industry. Due to the COVID pandemic, contacting the informants in the healthcare organizations was particularly challenging because the healthcare professionals were experiencing time constraints and burnout. The main source of data consisted of multiple rounds of 45-to-90-minute semi-structured interviews that were conducted over a two-year period, and the informants consisted of COOs, CIOs, project managers, data analysts, process designers, clinicians, and nurses (Table. 9). The reasons for involving multiple informants from varying roles within the organization is to triangulate the interview data from the informants (Dubois and Gadde, 2002) to minimize bias from certain members and to attain a holistic understanding of the entire healthcare organization.
Table 9. Distribution of the informants per healthcare organization and total number of interviews per roles

<table>
<thead>
<tr>
<th>Case</th>
<th>Management</th>
<th>Management/ Clinician</th>
<th>Management/ Nursing</th>
<th>Project Coordinator</th>
<th>Data Scientist</th>
</tr>
</thead>
<tbody>
<tr>
<td>HO (A)</td>
<td>3 (6)</td>
<td>1 (2)</td>
<td>2 (5)</td>
<td>1 (3)</td>
<td>1 (3)</td>
</tr>
<tr>
<td>HO (B)</td>
<td>1 (1)</td>
<td>1 (2)</td>
<td>1 (3)</td>
<td>1 (2)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>HO (C)</td>
<td>1 (2)</td>
<td>1 (2)</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td>1 (2)</td>
</tr>
<tr>
<td>HO (D)</td>
<td>2 (5)</td>
<td>2 (5)</td>
<td>1 (1)</td>
<td>1 (2)</td>
<td>1 (2)</td>
</tr>
<tr>
<td>Total # of Interviews</td>
<td>14</td>
<td>11</td>
<td>9</td>
<td>7</td>
<td>7</td>
</tr>
</tbody>
</table>

* HO = healthcare organization, # of interviews are in ( ) beside the distribution of informants

The interviews were mainly conducted via ZOOM (video conferencing software) due to the restrictions from the pandemic that prohibited close contacts with the participants and were further supplemented with in-person site visits after the restrictions were lifted. Prior to the start of each interview, the participant was asked to provide their consent; the interview only continued once the consent was given. Each participant was fully aware of the interviews being recorded and was provided with data confidentiality and anonymity disclosure to ensure a comfortable environment for the participant to enhance the accuracy of the information collected. Detailed notes were taken during the interviews, and immediately after each interview, the investigator transcribed the contents in the form of electronic documentation while listening to the audio and observing the video of the interview.

Semi-structured interviews were considered to be appropriate because they can help maximize the prearranged meeting times with participants such as COOs and physicians, with whom it is difficult to schedule multiple separate meetings. The investigator in charge of conducting the interviews endeavored to remain open-minded during the interviews to encourage a set of active data to minimize potential researcher bias while allowing for creativity. The informants were provided with the semi-structured interview questions prior to the interviews when requested by the informants; however, the interview process did not follow the same linear arrangement of questions. Instead, the interview process was flexible to allow
the informants to expand on their thoughts and expertise without feeling constrained by a rigid interview format.

While maintaining a high degree of rigor was of major concern, it was also important to avoid responses being predetermined by the research questions (Harley and Cornelissen, 2022). Data collected from the interviews were then triangulated with secondary sources, such as archival records, hospital websites, media reports, published blog posts from EHR vendors, and LinkedIn profiles of the key informants, to cross-check information. Some of the healthcare organizations were able to provide reports used within the organizations related to the deployments to confirm validity of their statements.

The notes taken during the interviews were used to supplement the transcriptions. As a validating procedure, after each interview, the informants were asked for their consent on follow-up emails and/or additional interviews to share the interpretation of what was said in the interview with them to avoid potential misunderstandings and ensure that the conclusions were accurate. Once restrictions for site visits were lifted, the researcher was able to join the informants during the morning clinical meetings, where the physicians discuss the plans for the day, review patient information, and share information between hand-offs of shifts; afterwards, the researcher was able to shadow the workflows of the physicians to observe the daily routines and the interactions with the BDA applications to inform decisions and actions. The data collected from the site visits were used to supplement the interview data and help the researcher visualize the care delivery pathway and the workflows of some of the informants.

The general strategy for analyzing the cases was to follow the guidelines provided by Yin (2018). We started with the initial theorization and concepts from reviewing the literature; hence, this study does not incorporate data analysis from the “ground up”. The research did not start with any specific theoretical propositions. Instead, it was guided by the phenomenon
of BDA deployment gap (phenomenon-driven) and the research question of how BDAC can be leveraged to address this BDA deployment gap for value generation in healthcare. We purposefully avoided setting any specific propositions prior to the analysis to facilitate insights from the data collected to surface organically and reduce the potential risk of researcher bias. We adopt the explanation building analytic technique – a type of pattern matching technique that is iterative in nature – which is a relevant technique for explanatory case studies and seeks to develop ideas for further study rather than draw conclusions (Yin, 2018). This research seeks to find potential “explanations” regarding the phenomenon of BDA deployment gap experienced by organizations in the context of healthcare, and this is depicted by the ‘black box’ that mediates the relationship between BDAC and value. The causal sequences of “how” and “why” BDAC can be leveraged to generate value is complex and difficult to measure, which requires further examination for further explanations. The explanation-building process was as follows, and the eventual explanations were from a series of iterations:

1. Making an initial but tentative theoretical statement(s) through preliminary theorization of the phenomenon of interest based on the literature and theory.

2. Comparing the data from the case study against the initial statement(s).

3. Revising the earlier theorization and statement(s).

4. Comparing the revisions from the first case with the data that came afterwards (second, third, and fourth cases), leading to further revisions.

5. Repeating this process (from step 2) with other cases as many times as needed.

There may be some criticism about this iterative process because it is partly inductive (revisions made based on the data from the case study) and partly deductive (pattern matching based on the preliminary theorization and concepts), which would render the objective of pattern matching as null because the final explanation may differ from the statements made at
the beginning of the study (Vaughan, 1992). This would be a fair argument if the study was a single case study because the revised explanation at the end may not be as convincing. However, we remedy this through applying the revised explanation to additional cases as part of the multiple case study, which would make the explanation more compelling and provide validations to the process. We reciprocate the statements of Harley and Cornelissen (2022) and conceptualize rigor not as an outcome of “proper application of a template”, but as an outcome of inferential reasoning processes. Hence, in the pursuit of rigor, we do not view the faithful adoption of widely used general multiple case study designs and templates as substitutes for rigor. Instead, we seek to supplement with a transparent illustration of the detailed iterative reasoning process that occurred during the multiple case study endeavour. We argue that there is no one-size-fits-all approach to qualitative study research and for the existence of inherent constraints with the use of generic templates (Köhler et al., 2022). As a response, we believe in the importance of adopting the approach of using multiple case study templates as a guide (with less emphasis on the “proper application”) and place a mindful emphasis on our quality of reasoning. The following section includes a more detailed case description of each of the healthcare organizations and the use cases of the BDA deployments.

4.3.2 Case Descriptions

The objective of this section is to demonstrate that the healthcare organizations selected as samples for the multiple case study have engaged in BDA deployments and developed BDAC. Descriptions of the four healthcare organizations used in the case study are presented in this section and summarized in Table. 8. Each healthcare organization consists of groups of multiple regional hospitals that offer different care services for their respective regions in Canada. All the organizations in the study have undertaken digitization of healthcare data, where a majority of the care areas have already changed to digital records completely. In
addition, the healthcare organizations have invested in BDA resources (e.g., data specialists, EHR systems, analytic tools) and have developed BDAC, albeit at varying levels, and utilize BDA applications as part of the care delivery process and decision-making across different area groups.

The use cases of BDA can be found in multiple forms of technology because each tool serves different purposes and can vary from as simple as EHR systems used as descriptive analytics to as complicated as artificial intelligence (AI)-driven real-time predictive analytics tools to predict the likelihood of a patient’s risk for death or intensive care (Table. 8). To bring more clarity to the wide range of BDA applications, EHR can provide BDA platforms to collect, store, and process the large volumes of disparate data in near to real-time, but it can also provide analytic capabilities in different forms of BDA applications within the EHR platform. Therefore, this thesis acknowledges that EHR can be distinct from BDA when it is viewed as a documentation and data warehouse for various BDA deployments, however, as it can have integrated BDAC within the EHR system, it can also be considered as a form of BDA application, albeit for more simple and general purposes. Top management support for BDA initiatives was observed from the organizational leaders through initial meetings and validated through secondary sources such as organization websites and third-party blogs of success stories. All the leaders of the healthcare organizations shared similar views in believing in the importance of incorporating BDA as part of the organizational strategy and the care delivery system. However, ongoing concerns were raised by the leaders related to the lack of value generated, even with access to large volumes of healthcare data and analytic capabilities by all four healthcare organizations.
**Table 10 Use cases of BDA deployments for each healthcare organization**

<table>
<thead>
<tr>
<th>Healthcare organization</th>
<th>Use cases of the BDA deployments</th>
</tr>
</thead>
</table>
| HO (A)                   | • Use of EHR system to collect, store, and analyze healthcare data.  
                           • AI-based predictive analytics to send real-time patient alerts.  
                           • Patient care design using BDA real-time patient condition tracking.  
                           • Reduction in prescription errors and medical errors from using EHR. |
| HO (B)                   | • Use of EHR system to collect, store, and analyze healthcare data (same as HO (A)).  
                           • AI-based predictive analytics to send real-time patient alerts.  
                           • Patient care design using BDA real-time patient condition tracking.  
                           • Reduction in prescription errors and medical errors from using EHR. |
| HO (C)                   | • Use of EHR system to collect, store, and analyze healthcare data (different to HO (A) and HO (B)).  
                           • Patient care design using BDA from real-time patient condition tracking.  
                           • Reduction in prescription errors and medical errors from using EHR. |
| HO (D)                   | • Use of EHR system to collect, store, and analyze healthcare data (older version of the one used by HO (C)).  
                           • AI-based predictive analytics for smart staffing, reduction in unnecessary ER visits, and patient flow patterns.  
                           • Patient care design using BDA real-time patient condition tracking.  
                           • Reduction in prescription errors and medical errors from using EHR. |

**Healthcare organization A – HO (A)**

HO (A) is the largest of the four (one of the largest acute care teaching hospitals in Canada) based on the number of beds, medical staff, and the variety of healthcare services provided for patients. This publicly funded healthcare organization initially transitioned towards the digitization of medical records approximately 18 years ago, using the ‘big bang’ approach,
where the organization attempted to convert all the paper format documentations and records into a new electronic system in a single phase with a short transition period. This adoption approach faced heavy resistance from the key stakeholders of the organization, and care providers experienced a difficult time adjusting to the new electronic system, which resulted in its initial failure. After the initial failure, the healthcare organization took the time to reassess the adoption strategy and decided to switch to a ‘phased rollout’ approach using off-the-shelf (OTS) EHR systems from vendors and has been on pace to complete the digitization of medical records in the majority of the care areas in the hospitals with a few areas still using the hybrid mode (coexisting of digital and paper forms of medical records).

HO (A) has invested in the BDA infrastructure and developed the analytics capability to extract, store, process, and analyze large volumes of healthcare data to generate BDA-based information outputs through BDA deployment initiatives such as EHR, real-time alerting, informed strategic planning, predictive analytics in healthcare, and reduction in medication errors through CPOE (computerized physician order entry). EHR allows for the collection of various forms of data (e.g., patient data, lab results, time number of clicks a physician took to order medication, etc.) and enables some analytics through the built in algorithms, where additional analytic functions can be purchased as through the EHR vendor. HO (A) implemented an alert tool that sends an alert when early signs of sepsis are detected before the patient actually develops a sepsis. This predictive analytics tool sends three different categories based on low, moderate, and high cases, which can inform the physicians and the nurses of possible septic shocks. Within the organization, there exist a separate information technology support (ITS) team and the decision support group for clinical analytics. The ITS team is responsible for analytics related to the organizational-level data, and how the EHR system as a whole is being optimally utilized (e.g., performance of a department on they use the EHR
system). Each hospital independently developed its own decision support department, which focuses on the clinical-level analytics and communicates with the end-users such as the physicians and nurses on the clinical side.

**Healthcare organization B – HO (B)**

HO (B) is comparatively smaller than HO (A) but would be considered a medium-sized organization offering similar healthcare service. It is a publicly funded religious healthcare organization and values providing high quality care as well as teaching and research. Areas of care include acute/ambulatory care (which includes disease management, urgent care, surgery, and medical imaging), complex care, long-term care, specialized mental healthcare, and rehabilitation. HO (B) started to implement the use of BD and adopted EHR around the same time as HO (A) and has faced similar challenges and trajectory in the adoption. The geographical location of HO (B) and HO (A) are close in proximity, serving similar patient populations; however, the organizations classify themselves as a separate healthcare organization. HO (B) purchased the same OTS EHR system as HO (A) to create an information sharing network in the future but remains to be siloed in nature with an independent organizational structure, information governance systems, organizational leaders, and decision support teams. Some of the BDA deployment initiatives include EHR, real-time alerting, informed strategic planning, predictive analytics in healthcare, and reduction in medication errors. A large emphasis from the HO (B) is placed on the collection of clinical information into the electronic system, and using the clinical information to enlarge the data base to improve the analytics capability with the organization. The organization has reduced medication errors through BDA deployments such as CPOE. Process of using BDA generally starts from a research question rather than practical implications, and a large emphasis is on using the analytics capability with the organization towards research purposes.
Healthcare organization C – HO (C)

The smallest organization of the four cases is HO (C), which has the least number of beds and medical staff. Compared to the previous two, the ‘big bang’ approach from the initial adoption of BDA and EMR, which first began in 2016, has been successful. The success is likely attributed to the size of the organization. The EMR system was purchased from a different vendor than HO (A) and HO (B) used, and in the case of HO (C), the organization continues to work closely with the vendor for the development of analytic tools and relies on their technical expertise as well. After completely transitioning to a digital system, the organization took a more stepwise approach for the BDA deployments through working with the provider of the EMR system to further develop BDAC. HO (C) emphasizes the importance of the use of BDA for research purposes, where a large part of the BDA resources is used to support the research teams. Areas of care include emergency care, mental health care, pediatric care, and surgical care. Some of the BDA initiatives are EHR, real-time alerting, and reduction in medication errors. Unlike the other three cases, HO (C) did not engage in the use of predictive analytics for clinical and operational purposes. Instead, the BDA deployments consisted mainly of descriptive analytics, which utilizes tools such as real-time dashboards with patient flow information for operational implications. Research projects have generally dominated the use of the BDAC for HO (C), and these projects are significantly impacted by the leading physician in the research field.

Healthcare organization D – HO (D)

HO (D) is the second largest of the four cases in terms of the number of beds and medical staff. The organization supports teaching and research along with clinical care. With strong support for a data-driven mindset from the leadership and members of the organization, HO (D) has experienced success with BDA deployments of various types, even without the most up-to-
date EHR system, where the members of the organization refer to the system as a “legacy system”. Like the other healthcare organizations, HO (D) uses an OTS vendor-provided EHR system, but the organization has its own data science and advanced analytics team that actively works with the clinicians, researchers, and hospital management to generate data-driven insights to help make ‘real-world’ decisions that improve patient care and increase hospital efficiency. HO (D) has a standalone full-service healthcare data analytics centre that is separate from the IT and decisions support group, which focuses on using BDA to solve practically relevant problems in the hospital. Both descriptive and predictive analytics are used in the BDA deployments. HO (D) supports various areas of care, which include critical care, children’s health care, emergency care, surgical care, long term care, and mental health care. BDA deployments include patient prediction, EHR, real-time alerting, informed strategic planning, predictive analytics in healthcare, smart staffing and personnel management, and reduction in medication errors.

The organization’s own advanced analytics department have developed nearly 30 different analytics solutions into the clinical practice. HO (D) have already implemented and produced machine learning models that are used at a daily, weekly, and monthly basis optimize the nurse resourcing teams and create better informed flow of the nursing teams. HO (D) developed an algorithm that can predict the number of patients that will come to the emergency department ranging from daily, weekly, and monthly predictions using large sources of disparate historical data. This tool also provides the distribution of low to high acuity patients that will come to the emergency department waiting room with high accuracy. HO (D) uses an AI-based BDA tool that monitors the patients at specific departments of the hospitals to warn the physicians based on low, medium, and high-risk patients at least 24-hours in advance if the patient is going to need intensive care or at the risk of death.
The different types of BDA deployments for each healthcare organization were identified from the preliminary interviews and secondary sources (e.g., news articles, websites, company reports). BDA deployments present in all four cases include EHR, real-time alerting, informed strategic planning, improved claim accuracy, and reduction in prescription errors, whereas the advanced form of BDA deployments that were based on predictive analytics using machine learning and artificial intelligence varied based on the BDAC of the healthcare organization. The list of BDA deployments presented in Table. 8 is not an exhaustive representation of all the BDA technologies across the healthcare organizations. These BDA deployments were purposefully identified to examine different forms of BDA technology used and the enabled processes and to create replication across the four healthcare organizations.

4.4 Analysis

We adopted the analytical techniques offered by Locke et al. (2022) to generate initial insights within each case and then compared through between case analysis (Eisenhardt, 1989; Yin, 1994). We describe four stages that took place to systematically go from raw data to theoretical implications and the logical reasoning processes that entailed. Although these stages are depicted as linear, it was an iterative process with the objective of strengthening the internal and external validity of the study, thereby improving the quality of our reasoning in pursuit of rigor in our efforts (Harley and Cornelissen, 2022; Langley, 1999).

4.4.1 Pilot Study

To develop the external validity of the phenomenon of interest, BDA deployment gap in healthcare, we use the extant literature (Chen et al., 2017) and a pilot study that consists of interviews with the leaders and data analytics specialists from a healthcare organization and healthcare data analytics service provider. The primary objective was to gain initial insights and confirm whether BDA deployment gap in healthcare was a prevalent issue in the real world
and that it was a matter of interest for practitioners. A secondary objective was to become familiar with terminologies used frequently by practitioners to make modifications to the preliminary semi-structured interview questions and to enhance the richness and comfortability of the conversations that would occur in future with the healthcare organizations. It was important to reduce scholarly jargon and use the terminologies that are more familiar to the informants. We decided to include a healthcare data analytics service provider in the pilot study because we believed that although our research interest lies with the healthcare organizations, if BDA deployment gap in healthcare is ubiquitous, the third-party analytics service providers would have had similar experiences working with healthcare organizations on BDA deployments and could offer wider perspectives on the phenomenon. In total, we conducted interviews with two participants from each of the organizations. The roles of the participants were CEO, CIO, and COO of their respective organizations.

Four critical insights emerged from the pilot study and were used to guide our multiple case study. First, all the participants identified the healthcare context as a key constraint and issue related to the adoption of BDA; they expressed frustrations over the slower pace of adoption in healthcare due to the complexity of healthcare systems. Each healthcare organization possesses varying resources, capabilities, routines, policies, and people; therefore, BDA deployments or initiatives that do not take into consideration the specific industry and organizational context face unexpected issues and dissenters. Therefore, both the external and internal context is important when considering BDA deployments in healthcare. Second, we found an unanticipated number of discussions over the importance of human factors and how the BDA tools were “used” by the end-users, which relates to the notion of affordance. Affordances are described as “potentials for actions that arise from the relationship between technical objects (e.g., BDA technologies) and goal-oriented users or group of users” (Lehrer
et al., 2018, pg. 430). Depending on various factors related to the end-users (e.g., experience, trust, objective), the leveraging mechanisms can vary and impact the value creation process. Lastly, we noticed that the informants were careful when using terminologies such as “return on investments (ROI)” and “financial benefits” when discussing values of BDA in healthcare, and efforts were made to indirectly discuss these topics. Lastly, when the participants of the pilot studies were asked to share their views on the availability of data and analytic capabilities present in the healthcare industry and organizations, all the participants noted that healthcare data is affluent, and the technology and analytic tools are available. However, the main issues are related to bringing the analytic models to real-world use with minimum disruption to the current healthcare delivery and customized to the needs of the end-users within the healthcare organization. These insights strengthened the external validity of the BDA deployment gap in healthcare phenomenon and provided a foundation to the development and modification of the semi-structured interview protocol, through preliminary theorization. HO (D) has seen improvements in clinical performances since the BDA deployments such as reduction in mortality rate and reduction in medication errors.

### 4.4.2 Develop Information Rich Case Descriptions

An information rich case study was developed for each healthcare organization which incorporated various types of data (Langley, 1999) to describe the organizational context, values and visions, list of BDA deployments, BDA infrastructure, and BDAC. Data analysis occurred in conjunction with the data collection, allowing insights and queries generated from the case analysis to provide guidance for future data collection (for the same case AND different cases). The insights generated from the analysis were then shared with the key informants during a follow-up meeting to ensure that our interpretations were accurate and portrayed in a transparent manner. A request for confirmation or additional documentation was
sent to the participants when we had further questions. These responses were voluntary; each participant was reminded at the end of each interview that there were no obligations to respond to the requests if they did not wish to do so.

Each interview was transcribed into a digital format and categorized based on the respective healthcare organization. Then, each participant was coded by their gender, general role, and specific title of the role. Prior to continuing with any further coding of the data, we carefully read through the entire transcript while watching the recorded video of the interview. This was done to capture the gestures, emotions, and facial expressions, which can provide helpful information in understanding the nuanced details in the data (e.g., frustration expressed when discussing working with the clinicians on certain initiatives). As we perused the transcripts, we continued to expand the depth and breadth of each case description. Three significant insights emerged in the process, which guided the subsequent analyses. First, the informants treated each BDA deployment as a separate entity, with many factors related to the leveraging mechanisms varying from one deployment to the next. They used words such as “depends”, “different”, and “based on” to emphasize that each deployment has its own specific conditions (e.g., stakeholders, scope, and intended value), which makes the value generation process complex and challenging. This insight led us to focus our analysis at the deployment level rather than the organizational level. Second, our initial interview subjects mainly consisted of top management, and as we were developing the cases, we noticed that the informants were referring to the end-users (e.g., clinicians and nurses) as the ones with the “power” or the “authority” to make decisions and take actions based on the BDA generated information. This meant that without talking to the end-users who interact with BDA deployments at the ground level, we would gain limited insights on the leveraging process of BDA in the healthcare organization. This insight led us to be mindful of “how” the end-users
interacted with the BDA-based informational outputs and used them to guide their decisions and actions. Lastly, the emergent preliminary insights suggested that the organization’s BDAC was discussed mainly from the processual perspective rather than the resource-based perspective. Hence, this led us to believe that it would be appropriate to distinguish between generating new knowledge resources and the knowledge development process in future analyses, with a greater degree of attention on the latter (Bogner and Bansal, 2007).

4.4.3. Categorize the Implemented BDA Deployments and BDAC Leveraging Mechanisms

We identified BDA deployments implemented in the organizations based on the list of BDA deployments in healthcare from the examples of real-world applications (Table 1). Our unit of observation was at the deployment or initiative level. Following the coding approach of Miles et al. (2018), we separated the coding process into the initial coding and secondary cycle coding using Nvivo to reduce the data into categories. The initial coding process incorporated an “analytic induction” process (Suddaby, 2006), where we went back-and-forth between induction and deduction. We tentatively coded the category of variables in the data according to the preliminary research theorization based on the extant theories and literature and reconceptualized throughout the data analysis stage. The initial conceptualization was guided by an established foundation supporting the interplay between BDAC and value or performance improvements (Gupta and George, 2016; Mikalef et al., 2020b; Wang et al., 2018c). Thus, we generated our initial list of codes focusing on BDA resources, BDAC, routines or practices, and the interactions between the end-users and technologies that were involved in the utilization of BDA-based information in the cases.

We mainly adopted the use of descriptive and in-vivo codes to capture the essence of the participants’ voices and the context during the initial coding phase. As the analysis progressed, we then clustered the initial codes into meaningful groups based on the ideas
generated, interpretations of the interviews, implications within the context, and the extant literature. The initial codes developed into 31 different groups, which resulted in clusters of codes that describe the structural properties – *rules and resources* – that were involved in the BDA deployments. These meaningful groups were further discussed amongst the research team, providing feedback to identify the developing patterns. During the analysis process, we identified patterns of technologies-in-practice and agents’ activities and further developed a granular abstraction that encompassed the interactional aspects of the agents with the structural components. Taking careful consideration of the similarities and differences between these groups, we identified nine *agent interactions (routine) principles* that were involved in the leveraging of the organization’s BDAC in the value-generation process.

4.4.4 Identify the Process of Knowing (PoK) Patterns

To answer the research question regarding how BDAC can be leveraged to address the BDA deployment gap to generate value in healthcare, identifying the agent interactions and routines was insufficient. We needed to investigate the mechanisms involved in the transformation of informational outputs from BDAC into decisions and actions that can generate value. We looked through the ten emergent themes, while pondering the question of ‘how these agent routines and their interactions with the structural properties are involved in impacting the knowledge sharing and transformation from BDA-based information outputs into operating outcomes.’ Concurrently, we went back and forth between the codes generated from the data and the existing knowledge management literature as a group (Locke et al., 2022). In the process, three major knowledge transformation patterns emerged, and we labeled these as *process of knowing (PoK) steps*: 1) BDA-based information to insights, 2) insights to operational understanding, which were present during the knowledge transfer and integration process, and 3) operational understanding of decisions and actions, where the knowledge
application occurs (Bogner and Bansal, 2007; Wu and Hu, 2012). This thesis will elaborate on these steps and the functioning elements in the subsequent findings (Section 4.5).

In order to understand the workings of the agent interactions that were observed in the form of routines in the three knowledge transformation steps, we grouped these routines into the corresponding PoK steps. For example, presence (or absence) of high information accessibility and visibility in the routines impacted the process of converting BDA-based

<table>
<thead>
<tr>
<th>Structural Properties (Rules and Resources)</th>
<th>Agent Interactions (Routines)</th>
<th>Process of Knowing Steps</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Effectively reducing the amount of information processing required by the end-users</td>
<td>Information accessibility and visibility</td>
<td>BDA-based information to BDA-enabled insights</td>
</tr>
<tr>
<td>• Understanding what and how (method) to display information to end-users</td>
<td></td>
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<tr>
<td>• Finding and moving the data needed for analytics</td>
<td></td>
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<tr>
<td>• Support from organization on incorporation from BDA for care practices</td>
<td>Information governance structure</td>
<td>BDA-enabled insights to operational understanding</td>
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<tr>
<td>• Leaders have been educated on the BDA model of the organization</td>
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<td></td>
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<tr>
<td>• Desired outcomes from BDA deployment clearly defined</td>
<td>Communication and coordination</td>
<td></td>
</tr>
<tr>
<td>• Clear outlined roles between analytics, IT, and clinical decision support teams</td>
<td></td>
<td></td>
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<tr>
<td>• Data literacy of the end-users</td>
<td>End-user driven insights</td>
<td>Operational understanding to patterned decisions and actions</td>
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<tr>
<td>• Strong commitment toward end-user driven BDA initiatives</td>
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<tr>
<td>• Applies practices that promote end-user engagement throughout the entire process of the BDA deployment</td>
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<tr>
<td>• Transparent communication between involved stakeholders on the desired outcomes</td>
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<tr>
<td>• Presence of liaisons for enhanced communication and coordination between data analysts and clinicians</td>
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<tr>
<td>• Efforts and commitment to keep effective communications between involved parties</td>
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<tr>
<td>• Matching insights with workflows of the clinicians and nurses</td>
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<tr>
<td>• Practices and teams in place to learn and understand clinical workflow and human factors</td>
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<tr>
<td>• Ability and willingness to deploy BDA initiatives without creating added workflows for end-users</td>
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<tr>
<td>• Focusing on use of BDA deployments for practical (solutions to real-life problems) purpose</td>
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<tr>
<td>• Collaborative ability to work together between data analysts, clinicians, and liaisons</td>
<td>Reciprocity</td>
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<tr>
<td>• Involvement of the clinicians in all stages of the deployment</td>
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<tr>
<td>• Developing method of building trust in the BDA deployments</td>
<td>Trust in BDA</td>
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<tr>
<td>• End-user trust on accuracy and reliability of the generated information impacts decision and actions</td>
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<tr>
<td>• Supporting BDA augmented decision making rather than BDA driven</td>
<td>BDA augmented decision making</td>
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<tr>
<td>• Duality nature of making BDA supported decisions</td>
<td></td>
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<tr>
<td>• Decisions and actions are solely conducted by the clinicians</td>
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<tr>
<td>• Improvements in clinical and operational outcomes through better informed decision making</td>
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<tr>
<td>• Able to transform operational understanding into creative pathways for decisions and actions</td>
<td>Critical thinking and clinical knowledge</td>
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<tr>
<td>• No autonomous BDA deployments in healthcare lead to need for critical thinking from clinicians</td>
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<tr>
<td>• Clinical experience and knowledge playing a critical role in leveraging of BDA</td>
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</table>

Figure 9: Qualitative data structure of the process of knowing steps.
information to BDA-enabled insights. There was a greater degree of manifestation of certain agent routines in our cases for specific PoK steps, which indicated that these interactions likely turn on or off as required based on the purpose of the activities. **Figure 9** shows the qualitative data structure of the cases.

All the cases share similar knowledge transformation patterns, albeit at varying degrees of frequency and rate. BDA-based information needed to be converted into BDA-enabled insight(s), which need to further transform into operational understanding prior to the enactment of the patterned decisions and actions by the end-users. This closely resembled the knowledge sharing capability in Spender’s (1996) view of systematic knowledge management and shared commonalities with the concept of ordinary and dynamic capabilities. In a similar manner, hospital knowledge capabilities follow the knowledge acquisition, transfer, integration, and application steps (Wu and Hu, 2012). These PoK steps make up the operational leveraging of BDAC.

4.4.5 Insights on Agent Interactions from Site Visits

At the site visits, the findings were shared with the key informants, who were requested to provide feedback to ensure our understanding of the PoK steps was representative of the real-world activities. A consensus was formed in agreement with the findings. Following the presentation of the findings, the researcher shadowed the daily workflows of the clinicians to observe their interactions with other agents (e.g., nurses, admin staff) and structures (e.g., BDA tools, alerts, and policies) in the moment at two out of the four healthcare organizations. Guided by the data gathered from site visits and the existing data, we identified three main groups of agents and the strength of engagements that were involved in the PoK steps: end-users (e.g., clinicians, nurses, decision-makers), data analysts (e.g., data specialists or engineers), and liaisons (e.g., clinical informaticists, change management team, quality initiative team). The
The word “liaisons” was used repeatedly by the informants to describe the agents or teams that play the bridging role to connect end-users with data analysts to improve overall communication and coordination. We made efforts to be mindful of the human agents involved in the leveraging process and the strength of these interactions that form the structure (Giddens, 1984).

Three levels of agent engagement strengths emerged in the PoK steps: *more engaged*, *less engaged*, and *as required* engagements (Figure 10). We depict the agent interactions and the strengths of each engagement, comparing the cases with more successful BDA deployments with less successful BDA deployments. The successfulness of the BDA deployments is based on the number of sustained BDA deployments in the healthcare organization. In all cases, the triadic relationship between the three agents was necessary during the first two PoK steps, whereas in the final PoK step, only the clinicians (end-users) were present. Based on the analysis, the greatest degree of capacity is required to convert the BDA-enabled insights into operational understanding given that more engagement in the interactions would require more capacity. In comparison, the conversion of operational...
understanding into patterned decisions and actions required the least amount of capacity, followed by the initial effort required to convert BDA-based information to BDA-enabled insights. In the next two sections of Chapter 4, each of the PoK steps and the agent interactions are further elaborated.

4.5 Findings

All the BDA deployments examined from the cases generated some type of informational output based on the organization’s BDAC, and to make a clear distinction between data and information, in this study, information refers to data that is processed into a form that has context and meaning (Davenport and Prusak, 1998). When the information can be used to make decisions and acted upon, this information is viewed as useable information, whereas when the information can be used to make value-added decisions and actions, we classify this as useful information. Healthcare organizations adopt various BDA deployments that can range from descriptive to predictive analytics to send useable information to the intended end-users. In turn, the objective is to minimize the amount of time spent finding and processing information by the care providers. As the CIO of HO (A) put it:

...clinical team spends an inordinate amount of time trying to get information and because how much time it takes to get the information, that reduces their time to think about the information or collaborate about the information or to consult with each other about the information.

[HO (A), Chief Information Officer]

The ability to have the information needed is essential for effective provision of care and impacts the care quality. Within the daily workflows of care providers, large amounts of information are consumed and processed. These can be in the form of patient health records, lab results, medical images, medication prescriptions, scheduling, and updates on patient conditions. Some are actively searched or requested, whereas some passively flow in and out of the healthcare system. The BDA deployments we examined intend to capture the actively
searched information and deliver it to the end-users in a digestible format to minimize the time pressure of the care providers and improve the information processing speed of both the passive and active information.

The EHR systems facilitate the BDA deployments by providing the large sets of data required for analytics, which was not possible with paper documentation. Therefore, the adoption of EHR was the first necessary step to building a data warehouse and served as a foundation of all BDA deployments in the four healthcare organizations. As one interviewee put it,

"You cannot analyze data points that are not being entered electronically... I would say number one, have all your data electronic and accessible in some way. When you are first starting with big data analytics, you don’t have to have everything to do your analytics, but what you are going to do with analytics, you have to have all of that data."

[HO (A), Clinical data strategist]

For healthcare organizations located in Canada, there was an added layer in the configuration process. Market leading EHR vendors were from the US, where many analytical offerings in the EHR systems came standardized to fit the needs of US healthcare organizations. This limited the immediate use of the EHR system right out of the box. All four healthcare organizations had to customize the software to meet their organizational needs and analytic purposes and to fit the healthcare system in Canada. For example, the built-in analytic feature that measures the performance of clinicians per revenue was not useful for Canadian healthcare organizations because this was not a priority measure of performance.

"Well, we certainly still do billing, (but) it’s not the main focus, so a lot of the out of the box analytical kind of offerings that come with the EMR (EHR) actually (is) not that useful to Canadian hospital and that’s both on the operational side and the research side."

[Technical Director, HO (C)]
Additional customization of the EHR system was required for each organization, and it depended on the care providers’ requests related to the features, flexibility, and needs. In the process of moving away from the traditional paper-based system, care providers gave up flexibility in documentation for standardization, and the burden increased because part of the administrative and documentation work that was regularly offloaded to administrative staff could not be offloaded with the EHR system. The administrative staff no longer had the authority to document the charts, resulting in a larger documentation burden on the providers. To mitigate this concern, HO (A) and (C) offered some flexibility during the implementation stage to reduce the potential for burnout from increased work efforts in using the EHR system and slowly expanded the standardization process as the system matured. We observed two different iterative modes of customization during the implementation of the EHR systems: 1) to the type of healthcare system and 2) to the care providers, and that the BDA deployments in our cases build on top of the EHR as the core foundation.

The following findings sections provide detailed elaboration of the structural properties and agent interactions involved in each of the PoK steps observed during the data analysis. The general layout of the findings section follows the structure of the qualitative data depicted in Figure 9. Each PoK step is broken down to the constituting structural properties, where the patterned interactions between structural and agent elements were found to be present.

4.5.1 BDA-based Information to BDA-enabled Insights

4.5.1.1 Information Accessibility and Visibility

Within healthcare organizations, many types of data are generated, and the implementation of an EHR system provides the digital platform to combine patient medical data with various other forms of clinical, operational, and financial data. This enables BDA deployments to have a higher level of analytic capability. The general perception towards BDA-based information
is that it is useful, and it is often assumed that the information will be used by the end-users to make better decisions and take actions that lead to improved operational outcomes. In our research, whether the information is used to make value-added decisions and actions in the care service efforts depends on the activities and interactions that occur during the knowledge creation and transformation phases. Surprisingly, a large portion of the useable information from BDA deployments was being ignored (the information was not consumed) or only viewed (consumed the information but took no action). This was observed for the real-time alert in HO (A) and (B), where the end-users (e.g., clinicians, nurses) were clearing alerts away without absorbing the information due to information being redundant, absence of urgency, or alert not actionable due to either the lack of authority or delivery to the wrong decision-maker. Concerns were raised by various participants, particularly top management, and data specialists. An interviewee from one of the HOs described this challenge:

_We have a lot of data, and we have a lot of reports that are nice to look at... they offer some insights, but until you take action, make a decision, make a change, it really is just some numbers on a page... we’ve got over 2500 scripts that run out of our vendor directly, and that’s not even accounting the various decision support departments at all our hospitals generate... there are tons of reports, but it is of no value until someone does something with it._

[Clinical data strategist, HO (A)]

To address this concern, we found that the HOs engage in efforts to optimize the process of transforming useable BDA-based information into useful insights. The first step was to increase information accessibility and visibility. HOs often used practices to better understand what (“information that the care providers actively seek for”) and how (“delivery method that the care providers can effectively use”) to display the BDA-based information for the care providers, which were undertaken prior to the BDA deployments. When HO (D) deployed its predictive analytics tool, which uses AI to predict if a patient is going to need intensive care or
die at least 24 hours in advance, the human factors team reached out to all the care providers ("more than 50") that would use the tool to understand their needs and priorities. This resulted in the organization of aggregated information required by the care providers, which effectively reduced the information processing efforts needed and eliminated the non-value-added information. Rather than selecting a small subset of the key leaders or decision-makers to choose what feels important, HO (D) used the time and resources to consider the needs of all the potential end-users of information generated from the predictive analytics tool. Contrary to the common perception that the information visibility increases with greater information accessibility and availability, we observed that it can actually lead to information obscurity and isolation if it is not purposeful. Take this example by the VP of the advanced analytics team at HO (D):

*The problem that you have is that if you have a very messy dashboard that doesn’t incorporate human factors considerations, you’re going to have something that might be needed by couple of people, but it’ll be hard for others to decipher. Whereas what human factors team does is, who are your end-users, don’t ask just the two or three people, ask all of them, and keep it really simple and keep it to the point.*

* [VP of advanced analytics, HO (D)]

Once the human factors team and care providers worked together to identify and prioritize the information needed, the integration governance team quickly pulled the data from various sources for the analysis. HO (D) created a separate team specializing in finding the right data at the right time to enable the modeling and development of BDA tools for deployments. This team provides the data pipelines for the advanced analytics tools. Generally, neither the data analysts nor integration governance teams fully understand what information would offer insights for the care providers. In parallel, the care providers rarely understand the type of data available for analytics and ways to find and move them.
In HO (D), the human factors team works to support the integration governance team to better understand the information that is actively required by the care providers. As such, the process of finding and moving the data needed improving. Although this practice initially consumes more resources, the potential negative impacts (e.g., alert fatigue, disruption of workflow) on the care providers due to excessive inputs of information can be significantly reduced. This also improves the efficiency of the data analytics team’s work efforts. An interviewee at HO (A) explains the post optimization process that had to take place when this practice was absent:

_There were a lot of alerts that were firing for pharmacists, providers, and nursing, and all sorts of stuff. (Care providers) were saying, ‘I do not need to address this... this alert is not valuable to me’. We did see the difference between the ones that they were just blowing past and the ones where they stop to change their process. (To resolve this) we worked with the clinicians in this case... we brought those ridiculous amounts of alerts, and said ‘here are the top 10 that are firing the most often, and are overridden 100% of the time’, and the pharmacy group agreed on what to turn off, what to turn down, and what to tweak..._

_Clinical Data Strategist, HO (A)]

Healthcare organizations in our study utilize standardized forms of practice to ensure that the BDA tools prioritize information that is needed by the end-users and minimize the surplus of BDA-based information that is 1) prioritized only by a small subset of the end-users, 2) overburdening, and 3) unnecessary. The key factor was to do this both prior to the BDA deployment and after the deployment in an iterative manner due to the inherent variability that exists in the information needed by the end-users in healthcare.

4.5.1.2 Information Governance Structure

Having a well-defined set of rules and guidelines on who manages information is essential in facilitating the roles of the agents and the procedures involved in the creating, processing, and accessing of information over its life cycle. This is particularly relevant in healthcare because the information is continuously processed and shared amongst various care areas. To provide
care, the care providers require specific information that is relevant to the patient they are serving, and the speed and accuracy at which this information is delivered can greatly impact the care outcome because it can enable (or disable) the possibilities of decisions and actions that can be taken.

Each HO uses various practices to develop their ability to handle the exponentially growing amount of information, and the collection of these activities become the building blocks to their information governance structure. HO (A) and (B) have two main departments that handle information, which are usually separated based on the scope of the BDA deployments. The first, department A, focuses more on analytics and reports used at an organizational level and more “action generating” layers of the organization. This relates to how the analytic tools built within the EHR system are used by the HO (e.g., numbers of users, time spent to complete a task, alerts being ignored) and the workflow efficiency of the frontline staff, coordinators, and managers within the EHR space. Department B handles more of the patient care level analytics and clinical information outputs. The two separate HOs adopt a structure where each has its own department B but share the department A because both HOs use EHR systems purchased from the same vendor. The intention was to create a system where information can easily be shared between the two organizations, thus resulting in a less siloed information governance structure. Contrary to the initial intentions, we observed that this structure brings confusion and role ambiguity amongst the organizational members, thus creating a disconnect in the flow of information in various levels of the organization. Interviewees at both HO (A) and (B) shared similar frustrations regarding the lack of clear explanations to why this is the case:

*From our perspectives, we would like to go to one decision support model really... but they’re not shared organization. We have shared electronic health record, but each organization stands alone as a separate organization. It’s not a great model, I don’t think anyone is going to tell you that this is the way we should be doing decision support... it does*
kind of make (it) a little disjointed process because it’s not all combined and it’s not ideal.

[Manager of Clinical Informatics, HO (A)]

There are number of different areas that are involved in pulling data and generating information that people (care providers) could go to, but it is fairly decentralized and little bit ad hoc in nature right now.

[Director of Information Technology, HO (B)]

If you can have one source to point them to and that takes them off (of the confusion) because we’ve got 5 different data warehouses, and it’s a lot.

[Clinical data strategies, HO (A)]

Both departments have the access to extract and manipulate healthcare data from the same sources; however, they do not have access to the same type of information. From the care provider’s perspective, the boundaries between the roles of the two departments are unclear without an established policy that explains the type of information each department has access to. There are multiple avenues to request access for BDA-based information, but since the boundaries between the two departments’ roles were blurred, time-sensitive requests would often bounce back or be transferred to someone with access to information, which results in additional work.

In contrast, HO (D) uses a single information governance structure, where one department oversees the information and provides advanced analytic solutions for the entire organization, encompassing both organizational and clinical levels. This team is part of HO (D) but maintains its own data warehouse that is separate from the central EHR system, and the purpose of the team is to provide BDA-based solutions for operational and clinical challenges. The team works with stakeholders within the organization who identify challenges in the care services or practices for which the advanced analytic department may provide solutions using advanced analytics. To be specific, this department uses data and advanced analytics such as machine learning and AI to advance patient care, improve efficiency at hospitals, and improve
patient outcomes. As stated by the VP of the advanced analytics department from HO (D), this department is not research focused:

*We can come up with fancy models and that’s where a lot of people stop, and they’re not really meant for deployment, they are more of nice research projects. That’s not what we want.*

[VP of advanced analytics. HO (D)]

The objective of the department is clearly stated on HO (D)’s website and uses a set of rules and policies to explicitly reflect the role of the advanced analytics department within the information governance structure to the stakeholders. Information requested from the care providers and other stakeholders needs to be oriented to solve practical real-world problems and deployable within the hospitals. Thus, the BDA-based information generated from the deployments had a higher probability of leading to the generation of useful insights.

When requesting a BDA-based solution in HO (D), end-users are required to fill out a standardized online form with rows of boxes dedicated to a single question (“what is your primary outcome metric?”), which is used to prioritize the resources of the advanced analytics department. The form provides a limited number of choices with the last choice listed as “other”. These choices are determined by the advanced analytics department and have been purposefully listed in priority sequence with the highest precedence outcome at the top. The outcome metrics in the form directly reflect the values that HO (D) seeks to attain from its BDAC. Resources are often scarce in healthcare, especially in Canadian hospitals. In HO (D), the decision to allocate the time and resources for BDA deployments was solely with the advanced analytics team, and this was fully supported by the leaders of the HO. Based on our observation, the members of HO (D) have a clear understanding of the process and commitment required to gain access to information from BDA, and this was made possible
through an explicit single information governance structure that enables the effective flow of information.

4.5.1.3 End-user Driven Insight Generation

In the process of generating BDA-enabled insights, we observed interesting dynamics between two groups with highly specialized knowledge: care providers (e.g., clinicians, nurses) and data analysts. The relationship between the two groups demonstrated similar characteristics to a client and service provider relationship. Data analysts provide BDA-based solutions in the form of BDA deployments for the problems – either for research or practical purposes – voiced by the care providers, whom are the end-users of the BDA-deployments and the information generated from them. As a couple of interviewees put it:

*We (data analysts) make sure that we are trying to solve a problem that the clinicians voiced, try to make sure that the solutions we propose meets their needs.*

[Director of data governance, HO (D)]

*(Care providers) would submit a request to the warehouse team, then we would meet and discuss the details of the requests.*

[Director for research informatics, HO (C)]

More often than not, a service provider-client relationship entails the provider driving most of the servicing efforts and offerings, where an acceptable level of service can be provided with minimum engagement from the end-users. This is rarely the case in the interactions we observed in our study. We find the presence of high engagement from the end-users in the process of creating BDA-enabled insights. Strong commitment was required from the care providers throughout the entire process of the BDA deployments, starting from the development of the analytic models to silent deployments, then to large-scale deployment that is followed with iterative feedback and modification of the existing model. However, the
demand of workload on the care providers makes this extremely challenging because overburdening can lead to burn out, decreased productivity, lower job satisfaction, and lower engagement.

To support end-user engagement, HO (A) and (C) adopt a top-down approach. This decision was based on their experience with previous change management processes, where areas with the most successful changes started with greater top management support. Starting with the identification of senior leadership and generating buy-in, HOs (A) and (C) worked their way down the organization structure to identify the clinical needs by engaging the frontline workers. However, the organizations reported that even with the senior leadership support, resistance at the clinical level remained. The ‘bigger picture’ problems that top management considered important were often not of greatest importance to the front-line staff, and without recognition of the problems experienced at the shop floor level, the practical challenges related to the use of BDA were largely being ignored.

In addition to top management support, which greatly impacts the organization’s overall direction and inclination towards the use of BDA in the provision of care, we observe another form of leadership support that was prevalent in the success of BDA deployments. The following statements by interviewees show the importance of leadership support on the level of end-user engagement with the BDA deployments; however, the leadership support in this context does not refer to top management support.

*The funny thing is that when we look at the leadership within the areas where we had struggles, those were also the areas that we would say that the leadership support was the weakest.*

[Manager of clinical informatics, HO (A)]

*You would want a clinical champion to facilitate that and get everybody on board to ensure that the information is actually being acted on.*

[Technical Director, HO (C)]
Rather, it refers to support from the shop floor-level leaders within the respective area groups where daily interactions with BDA deployments actually occur. These leaders may hold explicit titles or authoritative roles within the group or could be the most active advocates of BDA deployments from the same rank. In sum, for HO [A] and HO [C], leadership support in the functional care area groups was very important in attaining end-user engagement.

Another way to secure end-user engagement is to systematically make the users want to use the BDA-based information, creating changes in behavior of the end-users. HO (D) fosters the engagement through a simple practice, an open call where any member (e.g., clinicians, administrators, or any decision-makers) of the hospitals can identify problems that can be solved with BDA-based solutions. The policy is that the advanced analytics department does not propose anything, and it is entirely up to the end-users to drive the BDA solutions. This practice instills the end-users with a greater sense of responsibility and empowerment and serves the role of a contract between the service provider (data specialists) and client (care providers) regarding the commitments required in the coproduction of insights. The end-users understand their active role in the generation of BDA-enabled insights, which is well represented in this statement by one of the clinicians from HO (D):

_We (clinicians) are creating the data analytics, so we propose ideas to them (advanced analytics team), and then we work with them to find out what is going to work._

_[Clinician, HO (D)]_

The conversion of BDA-based information to BDA-enabled insights also improved with the presence of data literacy in the end-users. Data literacy is commonly understood as the ability to comprehend (read, write, and communicate) data and derive insights. Informants often used it to refer to the understanding of what is possible with the organization’s BDAC. A wide spectrum of data literacy was present. On one end of the spectrum, the end-users with better understanding of the information they are looking for and what was possible with
analytics had intelligible conversations with the data analysts. These stakeholders had more frequent collaborative efforts with the data specialists in the development of BDA deployments, which resulted in more customized BDA-based information for the end-users. This effectively translated into increased generation of useful BDA-based information. However, we also observed significant challenges on the opposite end of the spectrum, where without appropriate education and training on the organization’s BDAC, end-users frequently demonstrated a low level of data literacy. This often leads to overestimated expectations of the potential use and value of BDA in healthcare from the end-users and other stakeholders within the organizations.

4.5.2 BDA-enabled Insights to Operational Understanding

4.5.2.1 Integration of End-user Workflows

Healthcare is a highly routinized working environment, where functioning of care services is built on layers of patterned work activities. Informants in our study refer to these collections of activities as workflows. Care providers develop routinized workflows, following the best practices set by the institutional and organizational guidelines to deliver the highest possible level of quality care and patient outcomes. In an ideal situation, BDA deployments and the use of the BDA-enabled insights should enhance end-user workflows, not detract from them. Our study shows that when end-users experience considerable disruptions in their already “chaotic” workflows due to the influx of information, regardless of the insight, it is rarely accepted.

Regular forms of active confrontation (requests for modifications) and passive resistance (ignoring and not using) were detected from the end-users when the BDA-enabled insights resulted in interruptions in their workflows and additional workloads. As noted by one of the interviewees:

_You can’t change the workflow, you’d be dreaming if you think you (BDA) could change some of these workflows, (end-users) will just ignore it… if data analytics could give us more time back then we would be happy to change our workflow but right now, a lot of analytics stuff is _
sucking away our time...If you raise any friction or hurdle, or you say, 'just log into this website', people (clinicians) are not going to do it, so you have no choice but to adapt to their workflow if you want (them) to use your tool.

[Clinician A, HO (D)]

BDA implementation results in either the use of the same method of information consumption in a new form and/or adoption of new ways to consume the same type of information. This means that some form of disruption is likely inevitable. Therefore, it is important to find workflow integration practices to mitigate these frictions. HO [B] brings in additional resources in the form of subject matter experts with both technical and clinical knowledge to carefully approach the end-users on the floor level. By bringing in another group that is outside of the dyadic relationship to provide guidance and play a mediating role, HO [B] was able to better connect the BDA-based insights with the end-user workflows without creating significant disruptions and additional burdens on the care providers.

The difficulties faced by the data specialists in understanding the workflows of end-users are effectively reduced by the presence of subject matter experts, and the care providers were given assistance in the moment of their workflows, which helped in integrating BDA-enabled insights with minimal disruptions.

Similarly, HO [D] incorporated human factors experts and a product development team to shadow the end-users in the ward for days to weeks to learn the dynamics of the current workflows at the floor level where BDA is deployed. HO [D] places great importance in understanding the workflows of end-users to ensure that the use of BDA is integrated into the existing workflows. Through agent interactions such as shadowing, small group meetings with end-users, and relationship building through open discussions, HO [D] identifies optimal care pathways that can effectively leverage the BDA-enabled insights without creating disruptions.
This form of knowledge sharing process occurs iteratively between the agents, which enables integration of BDA deployments into the workflows.

HO (A) uses BDA tools within the EHR system to gain insights on the workflows of the clinicians to identify the clinical areas with inefficiencies in accessing and using the BDA tools deployed. The large data base within the EHR system keeps track of end-user information about how they are interacting with the tools in the system in real-time (e.g., time spent to complete an order, number of clicks, total time spent on procedure, and usage rate). Using these metrics, HO [A] identifies different groups of end-users that are struggling to leverage BDA tools, then brings in subject matter experts to visit the sites to provide support for the end-users in the moment of their workflows. In doing so, a large part of the workload pressure is removed from the end-users because there are no specific mandatory training sessions that must be attended; this also lessens the feeling of inadequacy from the care providers in their ability to use the BDA tools.

4.5.2.2 Communication and Coordination

The process of implementing BDA is an iterative process, which naturally leads to countless interactions between various parties involved. A typical leveraging process of BDA in healthcare encompasses interactions between the data analysts and the care providers. This can be understood as a dyadic relationship between the data analysts that act as the service providers and the care providers as the client. In our study, this dyadic association was not as prominently observed in the BDA value generation processes. More often, the relationship consisted of three main agents: BDA service providers (e.g., data analysts), end-users (e.g., clinicians and nurses), and “liaisons”. The liaisons, within the BDA in healthcare context, typically refer to agents such as the product development team, clinical informaticists, subject matter experts, human factors experts, and clinical researchers. The presence of the liaisons
acts as a “bridge” (direct quote from the interviews) that connects the other two agents (data specialists and end-users) in this triadic relationship, which was present in all four cases. Interviewees frequently used words such as “liaisons”, “bridge”, “sits on both sides of the fence” and “connect” to describe their roles in this relationship:

_I am that link between ITS and what we have available technically and then giving it that clinical perspective, so I do have to kind of walk that fence, straddle both sides of that fence. I need to have the knowledge of the technical side, but I need to be able to translate that clinically and what it means for clinicians. I communicate with all groups within our organization._

_[Clinical Informatics Manager, HO (A)]_

These liaisons work in improving the communication and coordination between the data analysts and care providers in various ways. Having knowledge in clinical and technical skillsets, the liaisons demonstrated flexible communications with both the front and back-end stakeholders. HO (C) outsources subject matter experts from their EHR provider, who visit the hospitals periodically to work with HO (C)’s data specialists and clinicians for the implementation of BDA deployments. During the visits, the triad of agents hold regular meetings to go over the workflow layouts and prototype models together. While the presence of the liaisons enabled communications in the triadic relationship, overreliance was also observed, which can lead to agents defaulting to the liaisons as the primary mode of communication. In the long-term, this led to negative impacts on the organization’s overall communication capability because the communications between the data specialists and care providers continued to decrease with increasing overreliance on the liaisons.

Regular productive meetings increase the effectiveness and efficiency of communication in an organization. Meetings play a critical part in maintaining and facilitating the communication and coordination between the teams involved in the BDA deployments. This is also where a large part of the learning occurs for the agents. It is rarely sufficient to
fully understand end-user workflows just from the visits to the clinical areas or compilation of feedback, and it can be difficult to have a wide range of in-depth conversations with the end-users due to the nature of the chaotic work environment. During these conversations, agents within the healthcare organizations can build data literacy and share specialized knowledge from their respective domains as meetings bring together different teams into a single open place to collaborate and garner richer knowledge sharing between the agents. The care providers transfer their experience and knowledge to the data specialists, and the data specialists transfer and educate the care providers on the technical aspects of the BDA deployments. Through this process, new knowledge can be created as the care providers are able to better understand the BDAC of the organization, thus building data literacy, and the data analysts are able to learn personalized clinical needs, workflows, and potential constraints.

As stated by one of the interviewees:

*In time, those meetings get really condensed, and we can do a lot in 15 minutes because we know what questions to ask, what the concerns are, and they (clinicians) know what we would be concerned about.*

*Director of Data Governance, HO (D)*

The initial meetings generally require a greater effort, but with the increasing number of interactions, the length of meetings drastically decreases. This demonstrates the improving communication and coordination between the agents in the triadic relationship, which further improves integration of BDA-enabled insights with the workflows of the end-users. However, in reality, time was a limiting factor for many care providers, especially for activities that do not directly relate to patient care. From the care provider’s perspective, having frequent meetings throughout the entire BDA implementation stages (development, deployment, and post deployment) was a demanding task. Therefore, garnering engagement from end-users to partake in the creation of value from BDA proved to be a difficult task for the HOs, and without
end-user engagement, regular meetings are difficult to sustain, which makes improving communication and coordination particularly challenging in the context of healthcare.

4.5.2.3 Reciprocal

During the conversion of BDA-enabled information to operational insights, there was a noticeable increase in the number of engagements in the triadic relationship between the data specialists, end-users (e.g., physicians and nurses), and liaisons. The more frequent engagements were also stronger in the level of involvement required from the agents, which resulted in a higher utilization of their capacity. HOs experience the challenge of limited amount of available capacity in each of the agent’s workflows and the demand for greater strength in the level of engagements from the agents. We observed that the collaborative ability and attitude of each of the agents helped in mitigating some of this challenge faced by the HO, and this is referred to as a reciprocality, which is the extent in which an agent party reciprocates to the available capacity of another agent parties. Therefore, HO with higher reciprocality demonstrated more collaborative ability to work together between multiple teams within the organization, and exhibited more empathy towards the hardships and difficulties faced in each other’s daily work efforts. As the end-users, data specialists, and the liaisons have been involved in all of the processes of the BDA deployments, these agents understand the level of commitment and efforts required in the implementation of the BDA applications from each other. In HO (D), a strong level of reciprocality was observed between the agents involved in the BDA deployments, where the informants were caring and understanding of another team’s struggles. This was demonstrated through appreciation of the time and commitment from other agent parties, and the level of personal attachments towards working together as single team in the BDA deployment process.
4.5.3 Operational Understanding to Patterned Decisions and Actions

4.5.3.1 Trust in BDA

In healthcare, the complete ownership of decisions and actions related to patient care belongs to the care providers, particularly the clinicians. Whether BDA-based insights can lead to value-added decisions and actions can also vary depending on the level of trust the end-users have in the BDA deployments. This means that the results from the use of the BDA tools have variability depending on the care provider that receives the information. We observe that one of the main contributors to this variability is the level of trust in algorithms exhibited by the care providers. Some were more averse (or trusting) towards certain forms of technology (e.g., algorithms or AI) than others, and this impacted the likelihood of actions being taken based on these insights. Due to the variability of trust that exists in the end-users of BDA tools in healthcare, part of the generated insights naturally becomes lost along the way and even actively ignored.

In HO (D), varying levels of trust from the clinicians were exhibited on their AI-based predictive analytics tools that were deployed to predict specific health outcomes in the patient. Depending on the severity of the patient condition and health deterioration, clinicians receive alerts that provide insights on the patient’s health; appropriate decisions need to be made, followed by an action. As stated by one of the clinicians at HO (D), the actions taken by the clinicians based on the algorithms were impacted by the level of trust:

There seem to be very variable levels of trust in the algorithm, so clinicians who seem to trust in the algorithm were more likely to act based on the results. Clinicians who seem to have less trust in the algorithm were less likely to take actions based on the results.

...it can be hard to have and feel like there’s a lot of certainty (in actions taken based on information from algorithm).

[Clinicians, HO (D)]
One of the ways that HO (D) built trust from the clinicians was to validate the accuracy of the predictions by the AI in direct comparison with the clinicians’ decisions through a separate blind pilot study. By comparing over 3000 clinician predictions with predictions made by AI, the study shows that using AI along with clinician judgement performed better than clinician judgement alone or AI alone, and this helped to build trust and buy-in from the clinicians. HO (D) purposely did not emphasize the predictive performance of the AI alone because it can also lead to negative reactions from the clinicians if their decision lead to worse performance than the AI’s decisions. It is important to avoid making the end-users feel as if the BDA tools are trying to control their actions because the purpose of these decision support tools can easily be misunderstood. In the majority of the BDA deployments, HOs developed different methods of building trust by demonstrating the accuracy and reliability of the information generated for predictive analytic tools and increasing familiarity of the BDA tools for descriptive analytic purposes. Healthcare professionals are placed in a position where even small errors can lead to detrimental health outcomes for the patients, and to minimize these errors, the providers rely on their clinical expertise, experience, and competence built from training. Therefore, the level of uncertainty and trust can have a significant impact on their decisions and actions.

4.5.3.2 BDA Augmented Decision-making

The popular discourse in the use of BDA for decision-making is this notion of data-driven decision-making where data is used to inform and validate the decisions. In contrast, healthcare has traditionally relied on the use of evidence-based decision-making, which involves combining the knowledge acquired from the healthcare professional’s clinical expertise, patient preferences, and research evidence (best practice) that is available within the context. As part of evidence-based decision-making, healthcare professionals are trained to avoid
accepting research evidence at face value and to use critical thinking to make clinical decisions. Evidence-based decision-making embodies the process of recognizing the information needed, searching for the appropriate evidence, critically assessing the evidence, and incorporating the evidence into decisions. Therefore, it can be challenging for health professionals to readily accept the concept of data-driven decision-making because it may be viewed as something that goes against their training. In this study, we observed that in some areas of the decision-making process, care providers were more accepting of the BDA-enabled insights relative to other areas. Thus, the decision-making process was more nuanced than initially anticipated.

In the process of treating a patient, healthcare professionals perform diagnosis and prognosis steps. Diagnosis is the first step in patient care because it relates to the identification of the illness through the examination of the patient characteristics (e.g., symptoms, family history, lab data). In this step, the care provider absorbs a lot of data and information and tends to be more objective. BDA are much more efficient in aggregating these data points and generating the diagnosis, and the end-users demonstrated less hesitancy in following the recommended actions based on these BDA-based diagnostic tools. In comparison, in the prognosis step, which follows the diagnosis, the decisions are often subjective, especially when information is missing or insufficient. When prognosis was provided by the BDA tools, we observed a greater degree of hesitancy from the end-users to follow through on the information. It was crucial to understand the behavioral tendencies of the end-users to effectively integrate the use of BDA into their workflows, which ultimately leads to decisions and actions. HOs use the term BDA-augmented or supported decision-making to denote that the ultimate decisions and actions are solely conducted by the end-users. This presents the problem of duality in making BDA-augmented decisions, where BDA-augmented decisions can reduce the hesitancy towards using BDA-based insights to inform decisions and actions; however, on the
flip side, even accurate and validated insights can be disregarded depending on the end-user’s perceptions.

4.5.3.3 Critical Thinking and Clinical Knowledge

Generally, the healthcare industry strongly emphasizes the need for critical thinking skills in the daily decision-making of the care providers. Physicians and nurses make numerous decisions that are based on a combination of the clinical knowledge garnered from their experience along with critical thinking skills to provide the best possible care pathway for the patients. Thus, the ability to critically think and assess the situation is an essential skillset that is required by the care providers to handle the dynamic work environment and the large variance of patient conditions or needs based on their repositories of clinical knowledge. Even with a set of care plans for a specific illness or injuries, there can be variabilities in the patient characteristics, conditions, available resources, and these factors can influence the assessments of the care providers. The inherent nature of the healthcare environment restricts the implementation of any BDA applications with autonomous decision-making ability. As noted by one of the informants at HO (D),

*It (BDA tool) is not automated in any way, none of our tools, like that are and I believe, nothing is allowed to be that way... clinical end-users (are) who make the decisions, this is not in any way actually automated or triggers (on its own).*

*[Director of Advanced Analytics, HO (D)]*

One of the ways in which BDA and AI can generate value is through a complete automation of certain processes, which can provide benefits such as: greater consistencies, reduction in errors, and effective reallocation of resources. However, from the cases in the study, no complete automation was observed from the BDA deployments. In other words, the decision-making responsibility remains solely with the care providers such as the physicians and nurses.
The degree to which the BDA deployments were systematically and effectively integrated within the daily workflows for care provision is significantly related to the decision-maker’s critical thinking ability and clinical knowledge. Utilization of BDA augments the decisions through a different way of informing the decision-makers, it does not replace critical and clinical thinking, and this was noted by the informants from HO (A) and (B),

At the end of the day, the actions that nurse take with any piece of digital data, that’s their skill set, and that’s their critical thinking and it is not necessarily analytics.

[Clinical Data Strategist, HO (A)]

... it is really reliant on you, you got to use your brains, you got to be thinking critically and not (simply rely on machines), and that’s what I don’t like! When you build electronic records, a lot of people want things tasked, especially business analysts and the report (oriented) people.

[Professional Practice Consultant, HO (B)]

Prior to the implementation of the BDA applications, there was a limited availability of database-based evidence screening tools, and this has resulted in physicians and nurses relying mainly on clinical knowledge and “gut instincts”. In an ideal situation, the BDA applications should be used to confirm or deny these instincts in the decision-making process, thus, strengthening the clinical decisions made during the patient care pathway. Conversely, the end-users’ overreliance on these tools can lead the end-users to forgo on their critical thinking abilities and clinical knowledge, which can ultimately inhibit the knowledge development in the long-term. This was observed in HO (B) with two of their BDA deployments, a tool that predicts the suicide rating for mental health patients and an AI-based sepsis alert tool. To mitigate the symptoms of overreliance that some of the nurses were facing, HO (B) emphasizes the importance of using critical thinking during the nurses’ daily interactions with these tools through updating the guiding principles, user guides, and practice standards to incorporate and continuously remind the nurses of the fundamental requirements in their skills in effectively
using the BDA tools for decision-making. As stated by the professional practice consultant of HO (B),

... you still have to be saying, “hey, this patient when I screen them for suicide, they are coming down as low, but I know the patient’s history, and I know that they are quieter, I see their demeanor changing, so I think we still should be ranking them a little higher, keep the frequency advisory.”

[Professional Practice Consultant, HO (B)]

The patterns of greater reliance on BDA applications were observed more often with the novice or new physicians and nurses. It is difficult to assume that the novice care providers have less critical thinking abilities compared to the more experienced counterparts, however, there can be a gap in real-world experiences with different clinical situations and patients. For example, physicians and nurses out of school typically join with limited exposures to sepsis patients, thus, identifying the likelihood of septic shocks from the large pool of patient information and lab results can be more challenging compared to the more experienced care providers. The sepsis alert tool can reduce this job significantly for the physicians and nurses, but the end-users need to routinely reassess the information from the tool by using a combination of critical thinking and clinical knowledge. As discussed by a director of HO (C), the decisions and actions made by the physicians and nurses are heavily influenced by the experience and training, and as the frequency of interactions with the BDA applications increase during the medical practice, it also contributes to shaping new routines of medical practices for each care provider.

Physicians (choosing actions) is based on the experience and where they trained, who they trained with, and it is experiential as opposed to evidence driven. In fairness, people will adjust as they learn or as they become familiar or as things are really pushed but systematic implementation is the next big chasm. We are doing a very good job at evidence-based medicine, big data, and forming evidence-based medicine but we are struggling with the implementation.

[Professional Practice Consultant, HO (B)]
Without making conscious efforts to critically think, the end-users exhibited behaviors of overreliance on the system and constrains the learning that occurs through the decision-making process, which can result in stagnant growth in the clinical knowledge. These practices can help empower the newer generation of healthcare workforce, but if it is not managed appropriately, it can lead to a workforce that waits for the system for information and possibly lose certain authorization abilities in the future.

The notion of critical thinking was not something that needed to be constantly reminded and educated for the nurses in the past, instead, it was accepted as a skill that was necessary. With the advancements in technology, decision-making has arguably have become more convenient and accurate, thus, enabling the care providers to take better informed clinical care pathway based on their experience, intuition, and observation of the patients in combination with the BDA applications. However, it was observed that an absence of practices that instill critical thinking and clinical knowledge in the BDA-augmented decision-making process can also be dangerous, which could result in an unintentional coercing on the healthcare providers to become less knowledgeable and in control of their care practices or routines. It was also observed that the systematic hierarchy in decision-making structure that already existed between the physicians and nurses continued to stay as status quo even with the implementation of BDA applications. Thus, the existing power dynamic did not change, and majority of the decision-making powers still remained with the physicians.

The following section 4.6 discusses the findings from the multiple case study with the objective of answering the two research questions introduced in section 4.2 to better understand how healthcare organizations use BDAC to enable the functional-level changes in the care delivery process and identify the operational capabilities that are associated with the leveraging of BDAC. In addition, this empirical study seeks to advance five of the seven contextual
themes identified from the SLR from the OM perspective: (1) changes in the organizational structure from BDA adoption, (2) transformation of routines and practices through BDA implementations, (3) role of BDAC in data-driven decision-making, (4) challenges in healthcare data and information sharing, and (5) developing BDAC.

4.6 Discussion

The number of BDA deployments continues to grow in the healthcare industry with an increase in the amount of healthcare data generated (Galetsi and Katsaliaki, 2020). Healthcare organizations are investing in the development of BDAC and seeking creative ways to generate value through BDA applications (Brossard et al., 2022) as the industry transitions towards the era of “digital healthcare” (Agrawal and Prabakaran, 2020). BDA in healthcare is particularly interesting because the industry consists of the need to serve large volumes of patients at a consistent apt level of quality while offering enough flexibility to accommodate for large variances of patients and aiming to deliver high quality of care.

Traditionally, from the OM perspective, healthcare service has been characterized by high knowledge intensity and human judgment and adopts a job shop or batch process (Denton, 2013). According to the product-process matrix by Hayes and Wheelwright (1979), this process structure offers flexibility and is appropriate for low- to medium-volume products or services with high customizability. While the flexibility accommodates the large amounts of variability that exist in healthcare, it presents an inherent constraint to meet large volumes of demand for care service. Arguably, the use of BDA has the potential to alleviate these limitations in the healthcare system’s structure and allow healthcare organizations to offer high volumes of care while reducing variabilities in the process to improve operational outcomes, which can lead to better value for the patients in the form of quality of care, patient outcome, and cost reduction. To do this, it is vital to understand the relationship between BDAC and
value at a functional level and to examine the BDA-enabled capabilities that transform BDA-based informational inputs into useful decisions and actions.

Srinivasan and Swink (2018) define analytics capability as “organizational facility with tools, techniques, and processes that enable a firm to process, organize, visualize, and analyze data, thereby producing insights that enable data-driven operational planning, decision-making, and execution” (pg. 1851). The study further demonstrates that the analytics capability enables information processing capacity, which helps the organization gather data to produce insights (Srinivasan and Swink, 2018). This operationalization of analytics capability is consistent with the prevailing views on what BDAC is in the relevant literature. However, the current examination of the role of analytics capability in the OM literature does not elucidate what operationally transpires to produce these insights that enable the operational benefits and how the organization and its members gain the insights. Through the multiple case study, this thesis seeks to advance the current OM literature and understanding of what operationally transpires from BDAC by examining the leveraging of BDAC in the healthcare context at the functional level.

4.6.1 KM-Structuration Middle-Range Theorization of BDAC to Value

In contrast to general theories such as the RBV which have been frequently applied in the OM literature to explain a wide range of phenomena that falls under the umbrella of “resources” that leads to competitive advantage for organizations (Hitt et al., 2016), middle-range theories intentionally “incorporate a level of specificity that restricts their explanation of causal connections to a subset of phenomena operating within a given domain” (Stank et al., 2017, pg.7). The objective of theorizing at the middle range is to explain the phenomena of interest by focusing on specific mechanisms that result in outcomes within certain boundaries of context. As Stank et al. (2017) argue, middle-range theories are not a simple “contextualization”
of the general theories but are naturally deeply rooted in the context to enable the development of deeper understanding of the conditions under which the phenomena impact the outcomes and the mechanisms involved in the manifestation of the outcomes. By adopting middle-range theorization, our research started with the existing knowledge within the domain of BDAC and value research and consolidated well-observed empirical evidence from the multiple case study findings that reflect the contextual contingencies of healthcare to explain the operational mechanisms that leverage BDAC to generate functional outcomes that lead to value.

The multiple case study shows how healthcare organizations, at the functional level, manage the knowledge generated from BDA-based information, which is used to make better informed decisions and actions that can lead to improved or innovative operational outcomes. KM is the process of creating value from knowledge resources in the organization, and the findings from the multiple case study show that the PoK steps occur throughout the leveraging process of BDAC. This further supports the notion that knowledge can be viewed as both knowledge-as-resource (outcomes of learning) and knowledge-as-process (learning activities) and that both are required to generate value (Bogner and Bansal, 2007) in the healthcare organizations. The KM process involves continuous interactions between the elements (agents and structures) within the enabled operational mechanisms that leverage information generated from BDAC into performance outcomes, and this knowledge conversion process is advanced in this study.

Structuration theory (ST) (Giddens, 1984) has been used more often in the IS field compared to OM, where it has been used to understand the evolution of user interactions with information technology (IT), the organizational implications from these interactions, and how the potential consequences are dealt with (Bernardi, 2017). Pozzebon and Pinsonneault (2005) state that the application of ST can come with some challenges because the general theory is
complex and abstract in nature and difficult to apply empirically, but they argue that it offers significant value in generating a rich understanding of how “IT structural properties might ‘enable or constrain human action’ and the implications of the users’ interactions” (pg. 1456). The use of ST in this thesis adopts the structuring of technologies-in-practice by Orlikowski (2000) and advances it through further examination of the rules and resources instantiated in the use of technology in the form of BDA applications in healthcare. From the perspective of technologies-in-practice, the dual nature of structure (set of enacted rules and resources that mediate actions of the agents) is both the medium and outcome of agent interactions. Thus, the structure is both in the form of technology (e.g., BDA applications, information, tools) and the enacted patterns of actions (e.g., routines). For example, physicians and nurses do not perform the workflows in a vacuum, but in a continuous cycle of daily practices, these agents use the knowledge (tacit and explicit) of previous experience, interactions with colleagues, information available, real-time conditions at hand, and the best practices based on the quality standard. Upon consolidation and application of this knowledge, the physicians and nurses choose to “structure” the actions in the moment, and in doing so, iteratively instantiate and reconstitute the workflows and care delivery process. In a similar way, in the real world, the nature of duality exists in the agents as well. As the findings show, the physicians can either (1) choose to use or not use the BDA-based information, (2) use the BDA-based information deliberately or inadvertently, or (3) use the BDA-based information for intended or unintended purposes. Thus, structuration occurs during technology-in-practice, whereby “agents in their daily routines use technology, then through its use, the agents can enact new structure and technology” (Sharma et al., 2012, pg. 136). When the conditions for technology-in-practice
change, the use of the technology or information creates adjustments to the structure and agency.

With BDA deployments in healthcare, the changes in new structure and technology result in 1) new information consumed through the same forms or different forms of medium and 2) same information consumed through different forms of medium. BDA represents a technology in various forms and applications, and these tools can be used to solve both simple and complicated problems. In turn, BDA forms can change vis-à-vis (a) availability and (b) type of BD being analyzed and the type of analysis (e.g., prescriptive, predictive, or descriptive) given (a). The findings from the study show that the conditions for BDA usage can change depending on the purpose of BDA use (clinical vs. non-clinical or research vs. practical application), and end-user data literacy and affordance as the “possibilities for actions” from BDA can be accepted differently based on the users (Lehrer et al., 2018, pg. 595). Based on the BDA form and usage conditions, the leveraging mechanisms of BDAC may change. To identify and understand the operational mechanisms that transform useable BDA-based information inputs into useful decisions and actions, it is necessary to examine the elements (BDA agents and structures) and how these elements interact within the operational mechanism during the BDA-based business value creation.
The Discussion section combines the theoretical perspectives and conceptual frameworks introduced in Chapter 3 with empirical findings from the multiple case study to present a KM-structuration middle-range theorization of BDAC value generation pathway in healthcare through a mediating construct, BDA-eFC (BDA-eFC), which operationally leverages the BDA-based information inputs from BDAC to create value in the form of improved or innovative operational outcomes for care delivery (Figure 11). Under this KM-structuration model of BDAC to value, BDA-eFC consists of three PoK steps, where BDAC-enabled functional-level changes occur in the care delivery process through the interactions

![Diagram](https://via.placeholder.com/150)

*Figure 11. KM-structuration model of BDAC to value mediated through BDA-eFC in healthcare*
between structure and agents during the BDA-enabled KM process. Having elaborated upon on the explanations of the observed patterns of the PoK steps, this thesis proceeds to operationalize what constitutes BDA-eFC.

4.6.2 BDA-eFC

The findings from the study show that BDA-eFC, which is a capability (Helfat and Winter, 2011), can serve simultaneously and conditionally ordinary or dynamic operational value generation purposes. The conditions that are salient in business’ functioning are the context (e.g., institutional type/characteristics, organizational level/unit, etc.) and contingency (e.g., environmental factors, possible challenges/constraints, etc.). As suggested by Helfat and Winter (2011), dual-purpose capability can promote new product or service introduction as well as the improvement of existing products and services. While the popular literature views ordinary and dynamic capability separately in the BDAC value generation process, this study finds that the BDA-eFC can improve the efficiency of the current healthcare servicing efforts with either significant modifications and/or with little modification to operational systems. Thus, from a definition standpoint, the BDA-eFC encompasses the (1) ability to systematically leverage existing or insignificantly modify operating rules, routines, and resources towards some purposeful end (“ordinary” capability role) and (2) ability to systematically sense and seize upon emergent business change opportunities that require the leveraging of significantly modified or new operating rules, routines, and resources (“dynamic capability role) (Figure 12). This ability is founded upon the knowledge management facets from the PoK steps described in section 4.5.
During the PoK steps described in the Findings section, a subset of structuration occurs through the interplays between the structure and agency where transformation of BDA-based information to operational understanding occurs. This leads to decisions and actions that lead to the BDA-augmented routines and rules as improved or innovated operational outcomes (Figure 11). This study provides insights on the operational mechanisms and various functioning interaction routines between the structure (rules and resources) and agents (end-users) that can be conditionally employed along the different PoK steps to cultivate an ability to function towards potentially achieving some ordinary or dynamic operational outcomes that can generate value in healthcare. The knowledge conversations and applications that occur at the floor level as bundles of activities or routines instantiate structures at an organizational level, thus creating BDA-augmented culture and climate.
The existing management literature examines BDAC predominantly as firm-level capability, and there is a paucity of research that examines beyond the BDA techniques and tools to understand the relationship between BDAC and value in the extant OM literature. This study addresses both of these limitations by offering an OM perspective and explanation to understanding the value generation mechanisms of BDAC by identifying and exploring a dual-purpose capability in the form of BDA-eFC, which operationally leverages information generated from BDAC at a functional level to impact floor-level servicing routines in healthcare. The findings not only demonstrate empirical assessment of the relationship between the capability layers but offer insights on its impact on operational performance and its implications on the BDA deployment gap phenomena. Adopting the multilayer capabilities framework from (Csiki et al. 2023), Figure 13 incorporates the findings from this study to provide a summary of BDAC and BDA-eFC in healthcare.

Figure 13. Multilayer capabilities framework of BDAC and BDA-eFC at firm level and functional level in healthcare
4.6.3 Learning-based Development of BDA-eFC

The learning-based model of capability development has been prevalent in the management literature as one of the main explanations to dynamic capabilities (Cepeda and Vera, 2007; Wu and Hu, 2012; Zollo and Winter, 2002). Capability development within an organization is facilitated by three learning routines: experience accumulation, knowledge articulation, and knowledge codification (Zollo and Winter, 2002). As emphasized by Kahl (2014), these learning activities can take place within or outside the organization, and this relates to the organization’s reaching out to external sources of learning instead of relying on internal capabilities. For example, with the introduction of new technology, the healthcare organizations in this study brought in liaisons such as clinical informaticists or human factors experts to help articulate and codify BDA-enabled insights to facilitate building the knowledge-based resources that are explicitly expressed as practices and work efforts. One reason for sourcing external knowledge may be that healthcare organizations lack the ability to connect the two siloed groups of agents with different specialized knowledge. In particular, the care providers (e.g., physicians and nurses) are likely not accustomed to working with data specialists to develop new ways to design care delivery because the majority of their interactions occur with patients and other care providers.

With the introduction of BDA applications, new technical skills are required to understand and process the technology, which creates the need for data specialists. However, in the healthcare context, the end-users are often front-line care providers with specialized knowledge and skillsets and limited time and resources to learn new processes. This creates a disconnect in the knowledge sharing between the data specialists and care providers, which hinders the capability development. Organizations generally reach out to external sources to reduce the cost of knowledge articulation and codification associated with proper applications
of the routines (Zollo and Winter, 2002). To leverage BDA in healthcare, organizations are required to turn to two forms of external source of learning instead of relying on internal sources: 1) healthcare data specialists to initially understand and develop BDA applications and 2) liaisons to assist the transfer of learning to the care providers. This, in turn, creates a triadic relationship that requires greater coordination and communication, thus adding variability and complexity to leveraging BDA for healthcare organizations.

While the dynamic capabilities literature emphasizes learning processes at an organization level or upper level of management (Teece, 2014; Wu and Hu, 2012), OM encourages the examination of operational-level or functional-level learning processes (Browning, 2020; Csiki et al., 2023). This study further contributes by demonstrating a need to consider an additional layer of learning activities that occur in an organization with the implementation of BDA applications with AI-level learning. Amongst the different BDA applications and techniques, AI use in decision augmentation has shown AI’s ability to learn and train itself initially using a large quantity of data, and further improve itself through an iterative cycle using feedback derived from the decisions and actions taken based on the suggestions provided (Leyer and Schneider, 2021). Hence, in addition to the end-users and other stakeholders in healthcare organizations learning how to use the new technology, there is a separate self-learning algorithm that can continuously optimize itself based on the decision outcomes. The BDA-based outputs then reenter the PoK steps as new information inputs, thus resulting in further structuration at both the AI level and operational level. Decision-makers can draw from their own experience (e.g., clinical knowledge) and can learn from decision outcomes to inform best practices to collaborate with BDA deployments. This can be in the form of building trust and gaining confidence in the use of BDA applications and more effectively using BDA-enabled insights from technology such as AI to inform decisions and
actions. It is important to note that AI-level learning and training is inherently implemented by the designers of BDA applications, which ultimately means the managers are required to periodically assess and update the algorithms and make appropriate adjustments at an organizational level.

Just as learning can occur with the use of BDA, unlearning can occur for the end-users in healthcare, which can constrain the humans rather than enabling them (Leyer and Schneider, 2021). With the augmentation of processes enabled by BDA deployments, the care providers may face the risk of unlearning essential routines and skill sets that were part of the existing knowledge repositories. For example, the use of an AI-based tool to identify sepsis can help nurses and clinicians prevent patients from septic shock but can also lead to loss in the ability to identify sepsis on their own. Although this application provides benefits to the care providers, especially novice nurses with less experience with learnings from external sources, it can also lead to the unlearning of information from internal sources such as more senior nurses. The healthcare context has little to no BDA applications that make the decisions and actions on their own; therefore, it will be of managerial concern to ensure that core skills such as critical thinking and essential routines are not abandoned by the healthcare agents due to the increasing dependency on the tools.

4.6.4 Actor Role Ambiguity and Physician Centrality in Healthcare with BDA

Role ambiguity with key agents playing multiple roles in healthcare delivery can lead to various complicated managerial concerns and can result in agency problems when trying to find an alignment of interests between the agents. In healthcare, the patient plays the role of both the customer and input in the care delivery process and is heterogenous in nature (Sampson and Spring, 2012). Healthcare delivery is generally co-produced with the patients and several other providers, and an increasing number of “customers” have started to be
integrated and engaged in the supply chain in designing the delivery process (Dobrzykowski, 2019). BDAC can accelerate this process and enable healthcare organizations to effectively incorporate patient healthcare data to influence care experiences and outcomes. This, in turn, can reduce ambiguity in the role of the patients in the co-production process of BDA applications incorporating patient information into the network of the healthcare supply chain, and it can be utilized without demanding active engagement from the patients.

Arguably, from an OM perspective, more interesting changes occur in the upstream of the healthcare supply chain, where the integration of BDA may lead to further exacerbation of actor ambiguity for the care providers, in particular, the physicians. Within the healthcare supply chain, the physicians serve as service providers to the patients, suppliers for others, and also as end-users to some suppliers (e.g., government agency, care equipment, EHR). Naturally, in this supply chain network, the physicians play multiple roles and their decisions greatly influence the care delivery process. This leads to centrality of the physician in the healthcare supply chain and creates various agency dilemmas due to the dominant role of the physician in the diagnosis, prognosis, and treatment processes for the patients (Dobrzykowski, 2019). As noted by Schneller and Smeltzer (2006), decisions and actions taken by the physicians produce large variations in the materials (e.g., equipment used, drugs prescribed) used, even for patients with similar needs. Ultimately, physician decisions have a large impact on performance outcome metrics and the use of the healthcare organization’s resources and capabilities.

Leveraging of BDAC in healthcare adds to this complexity by introducing a new agent (data specialists) and one new form of structure (BDA-based information), which impacts two unique challenges that exist in healthcare discussed by Dobrzykowski (2019) related to (1) agency dilemma and (2) absence of coordination mechanisms. In addition to the common agency dilemma faced by physicians between the patients and healthcare organization in
ensuring quality service for the patient while reducing costs for the healthcare systems, this study draws attention to a new agency dilemma that can be found in the relationship between physicians, data specialists, and patients.

The most important responsibility for physicians remains the same even with BDA implementations, which is to ensure high quality service for the patients without overburdening the healthcare system’s resources. However, in the leveraging process of BDAC, additional responsibility is demanded from the physicians to use BDA in the care delivery process. With healthcare organizations investing significant financial resources in developing BDAC and top management support towards implementation of BDA in healthcare, physicians are pressured to adapt to the changes. In addition, new types of interactions occur with data specialists and liaisons in developing BDA tools and ways to effectively incorporate them to add value to the existing healthcare delivery packages or develop innovative ways to provide the same service.

From the physician’s perspective, use of BDA is not necessary in delivering high quality service, and it often requires extra work in the form of learning new skills, working with data specialists, frequent meetings, and providing feedback. Spring et al. (2022) posit that AI-systems can potentially increase professional-client interactions by “releasing professional’s time” to be spent on other value-adding work. In the context of leveraging BDAC in healthcare, we show that there is an increase in the interactions between data specialists, liaisons, and physicians that lead to work efforts that seek to exploit the potential of BDAC in improving operational and clinical outcomes. However, the physicians play the role of both the professional (delivering service to the patients) and client (receiving service from data specialists), further increasing the level of role ambiguity in the healthcare supply chain. In this relationship, physicians receive products and services from the data specialists that are designed to ameliorate the limited time and resources constraints via BDA tools that
make the care delivery process more efficient. More often than not, physicians are required to interact and engage more in the co-production of these tools to successfully leverage and generate value from BDAC. This can be counterintuitive from the physician’s viewpoint and may not necessarily align with the objective of delivering high quality service for the patients while optimizing the overall cost (for patient and organization), which can lead to more agency dilemma. Actor role ambiguity occurs predominantly in the first two of the PoK steps, and the increase in actor role ambiguity of the physicians can lead to greater agency dilemma which creates challenges in the transformation of BDA-based information to BDA-enabled insights and operational understanding. The challenges can be further exacerbated due to physician centrality in the PoK step three, where the entirety of the agent interactions is with the end-users, leading to limited conversion of operational understanding to patterned decisions and actions from BDAC.

Contrary to the general perception that BDAC primarily generates benefits for organizations, the dual nature of BDA can either improve or hinder organizational performance depending on how it is leveraged. This study contributes by empirically demonstrating that whether BDA implementations improve or worsen issues related to agency dilemma and physician centrality depends on the healthcare organizations’ routines that facilitate the PoK during the leveraging of BDAC. Thus, healthcare organizations are able to effectively utilize various practices and activities to leverage BDAC in reducing the existing challenges related to agency dilemma and physician centrality. First, the potential increase in actor role ambiguity of care providers can be curbed through off-loading some of the additional responsibilities of co-production of BDA solutions for care delivery to the liaisons. This allows the care providers to co-produce the BDA solutions with the data specialists “in-the-moment” of the everyday workflows, and because the liaisons are able to communicate and transfer specialized
knowledge from both data specialists and care providers, the need for a high level of data literacy from the care providers is reduced.

Second, information governance structure plays an important role in the transformation of BDA-based information into BDA-enabled insights in the first PoK step. Information governance structure dictates the agencies that manage “information artifact and how exactly it is created, stored, processed, and accessed within and throughout organizational boundaries” (Mikalef et al., 2020a). In the domain of IS, IT and information governance are a mechanism of allocating organizational resources into value-adding capabilities (De Haes and Van Grembergen, 2009) through structures, processes, and roles. As Weber et al. (2009) argue, information governance should consist of activities related to these three dimensions, which they describe as structural, procedural, and relational practices. In particular, relational practices are responsible for goal alignment and providing direction towards a strategic and operational objective (Mikalef et al., 2020a). Information governance has shown to positively moderate the relationship between BDAC and innovative capability (Mikalef et al., 2020a). Our study complements this with an OM view to expand the work efforts involved in information governance and how it can help in leveraging BDAC towards value-added outcomes. The presence of a clearly-defined information governance structure can reduce actor role ambiguity and minimize the impact of physician centrality by (1) institutionalizing the structures, processes, and roles between the agents involved in the leveraging of BDAC to align with the strategic and operational objectives for BDA deployments, (2) explicitly drawing organizational boundaries regarding who manages BDA-based information in the value generation process (e.g., physicians are required to submit requests and show commitment to effectively use BDA tools), which works as a relational coordination mechanism, and (3) enabling knowledge sharing between agent groups with specialized knowledge in developing
BDA solutions to care delivery, which in turn can spread the centrality away from the physicians through collaborative efforts and decision support tools.

4.6.5 Automation (Ordinary – Improved) and Augmentation (Dynamic – Innovative)

A popular discourse in the BDA research stream has been to draw a clear distinction between the concept of automation and augmentation, especially related to the use of AI applications (Tschang and Almirall, 2021). From a technology view, automation “replaces” the work that needs to be done by humans, whereas augmentation “enhances” the work efforts (Raisch and Krakowski, 2021). Following the trends of other industries, the use of AI-based solutions has been increasing in healthcare for both automation of simple routine tasks and augmentation of human work efforts and decision-making. Raisch and Krakowski (2021) adopt a management perspective to argue that automation and augmentation should be understood as interdependent concepts that are not separable, characterized by a paradoxical relationship. This comprehensive approach offers a nuanced understanding of how organizations use BDA applications, in the form of AI-based solutions, to create business value. The notion that augmentation and automation can complement (or impair) each other over time and space suggests interesting managerial implications for understanding the leveraging mechanisms of the technology-enabled system and the role of humans in the process.

Based on the fundamental OM concept of the product-process matrix, automated processes are designed to match higher-volume demand (Hayes and Wheelwright, 1979). AI-based solutions have long been used to automate routine tasks in operations and logistics (Raisch and Krakowski, 2021), and with the advancements in machine-learning techniques accompanied by the large increase in data, more organizations are finding ways to use them for managerial tasks. This study supplements prior research with an OM-inspired multilayer capabilities framework to introduce the potential role of BDA-eFC, a dual-purpose capability,
in further advancing managerial understanding of the tension between automation and augmentation from AI-based applications in healthcare. In dual-purpose capability, the dynamic uses “emerge later in the capability evolution” and can turn either on or off to serve ordinary or dynamic purposes (Helfat and Winter, 2011; Kahl, 2014). The case study data show that BDAC can be leveraged to generate both improved and/or innovative operational outcomes depending on various BDA forms and usage conditions in the functional-level processes. In the context of healthcare service, the complete automation of processes was rarely evident. The role of humans (e.g., physicians, nurses) in the leveraging of BDAC are emphasized, and the primary role of the structures (e.g., decision-support system, information) is to support or “augment” the decisions and actions made by the end-users through combining automation of some human tasks and enhancement of human knowledge and capabilities of the care providers. Thus, as Spring et al. (2022) suggest, augmentation of the enabled capabilities arise from a combination of releasing the professional’s time from automation, and then using that time towards collaborating with data specialists and BDA-based systems to create innovative operational outcomes. From an OM-based perspective, the new BDA-enabled routines from the increased collaborative work efforts positively impact the agents’ and organizations’ affordances of BDAC, which leads to greater efficiency in the existing routines that can release more of the care providers’ time in an iterative manner.

Even when BDA-eFC serves ordinary or dynamic value generation roles, similar PoK steps occur. It is important to note that automation and augmentation are observed as consequences of using BDA or AI-based systems, not as the overall outcomes. Rather, these concepts should be understood as processes that lead to different types of operational outcomes. These research findings add opportunities to go beyond the paradoxical relationship between automation and augmentation and identify potential mechanisms in which healthcare
organizations utilize the two processes to complement one another towards operational outcomes.

4.7 Conclusions

Relative to the degree of interest in BDA, the mechanisms involved in the value generation process of BDA in healthcare have largely been understudied. BDA has many potential and actual benefits for healthcare organizations through various deployments of BDA applications (Dash et al., 2019; Witjas-Paalberends et al., 2018). The SLR and the revised conceptual framework development (Chapter 4) suggest that BDAC has a mediated effect on value in healthcare and the BDA-based informational inputs must be operationally leveraged to improve performance. The multiple case study presented in this chapter further adds insight into understanding the ways healthcare organizations generate value from BDAC, including transforming BDA-based information into insights and operational understanding that can be integrated into every-day work efforts, thereby forming routines. In addition, this study identifies the interactions between the structure and agents in each step of the process of knowledge transformation from BDAC, as well as the strength of these relationships.

The study examines four healthcare organizations that have developed BDAC in Canada through in-depth interviews and field visits, which were used to identify common patterns within and across the healthcare organizations involving the main constructs and processes in the leveraging of BDAC in generating value. It is found that in all the healthcare organizations, BDAC is required to be further operationally leveraged to influence performance outcomes that can lead to value. This leveraging mechanism involves various steps of PoK that help in transforming BDA-based information into decisions and actions. Using process-based contextualization as the main approach to theorizing from case studies, this study is used to empirically supplement the insights generated from the SLR to offer a
KM-structuration model of BDA-eFC and contributes to better understanding of how organizations can generate value from BDAC in healthcare. The findings suggest that the BDA-eFC can operationally leverage BDAC to serve both ordinary and dynamic value generation purposes through knowledge management practices in healthcare organizations. Thus, BDA deployment gaps in healthcare may be attributed to organizations with BDAC facing challenges in transforming BDA-based information into BDA-enabled insights and ultimately into operational understanding and patterned decisions and actions.
Chapter 5

5. Summary of Thesis

Based on the initial conceptual framework developed in Chapter 2, a series of elaboration efforts were taken. The SLR (Ch. 3) was used to confirm the existence of the ‘black box’ that involves leveraging mechanisms of the informational outputs from BDAC to generate value, and the multiple case study (Ch. 4) was used to examine the nuances in the interactions between structure and agents in the leveraging process to understand the work efforts involved. The objective of this thesis is to answer the following overarching general research question:

**RQ**: How can BDAC be leveraged to address the BDA deployment gap for value generation in healthcare?

To address this expansive research question, in Chapter 2, the scoping review of the BDA research in the extant management literature was used to develop the initial conceptual framework for BDAC to value in a general context. This introduced a current gap in the literature, which demonstrated that the direct value generation view of BDAC to value is insufficient in effectively understanding the BDA deployment gap phenomena, and a possible ‘black box’ exists that mediates the relationship between BDAC and value. Thus, there was a need to identify and understand ‘what’ is leveraging the information generated from BDAC to understand ‘how’ this process occurs. These propositions along with the initial framework was then expanded through the SLR, which was then used to guide the development and analysis of the multiple case study in the context of healthcare.

The SLR conducted in Chapter 3 presents a systematic review of the literature on BDAC and value in healthcare. Findings from the SLR suggest that BDAC does not directly impact value and is likely mediated through different capabilities in the healthcare organization, and this has implications in its ability to function to achieve operational outcomes. This section
offered a revised BDAC to value framework in the context of healthcare and discussed constituents in the form of organizational capabilities within the ‘black box’ that is mediating the relationship between BDAC and value. Upon examination of the extant literature, it was evident that the direct value generation view of BDAC to value was insufficient in effectively understanding the BDA deployment gap phenomena and that there is a lack of empirical research work that seeks to distinguish BDAC (that generates informational outputs) with the ‘black box’ (that leverages the informational output from BDAC). The theoretical implication of the middle-ranged theorizing helped to provide a contextualized understanding to the propositions made in Chapter 2.

The multiple case study examined healthcare organizations with BDAC to empirically assess the conceptual framework developed and understand the mechanisms involved in the leveraging of BDAC, in particular, how the use of BDA in practice can be integrated into the functioning of healthcare organizations. The findings from the multiple case study reveal interesting insights. First, the process of knowledge conversion and applications from BDA-based information consists of three steps that convert (1) BDA-based information to BDA-enabled insights, (2) BDA-enabled insights to operational understanding, and (3) operational understanding into patterned decisions and actions. In the PoK steps, interplays between various agents’ interactions and structural properties resulted in routines that influenced knowledge conversion from BDAC. Second, these findings from suggest the presence of what this thesis posits as BDA-eFC, which operationally leverages the BDA-based information from BDAC to improve or innovate operational outcomes in healthcare organizations. Furthermore, this revealed the underlying mechanisms in how a firm-level capability (BDAC) can lead to value through a functional-level capability (BDA-eFC), thus influencing the front line or floor level routines that impact operational performance. It is important to realize that the improved
and innovated operational performance is what potentially leads to the generation of value in the form of care quality, patient experience, and cost of care. The multilayer BDAC and BDA-eFC model in healthcare offers a comprehensive understanding of the value generation pathway of BDAC from an OM perspective.

5.1 Contributions

By addressing the BDA deployment gap phenomenon from an OM perspective in the context of healthcare, this thesis contributes to the BDAC and healthcare OM literature, as well as managerial practice in a meaningful way. The following sections describe the theoretical and managerial contributions of this research.

5.1.1 Theoretical Contribution

One of the main theoretical contributions of this thesis is the identification of the operational mechanisms involved in the leveraging of BDAC in the creation of value. Through careful elaboration of the indirect relationship between BDAC and value, the research findings respond to the need to examine the different organizational capabilities through which BDA can lead to value, raised by Mikalef et al. (2018). The presence of BDA-eFC can help explain the process in which BDA-based information from BDAC is converted into knowledge resources and knowledge processes (e.g., learning) that generates operational outcomes. The identification of the mediating dual-purpose capability can help advance closing the gap in the growing BDA literature and offer insights on different ways in which BDAC can lead to value. For example, section 4.6.2 of this thesis offers an operationalization of the construct that mediates the relationship between BDAC and operational outcomes (that can lead to value) through improved or innovative outcomes. This demonstrates that the functional capability can have both ordinary and dynamic purpose depending on the conditions present during the
interactions between structure and agents within technology-in-practice (e.g., type of technology, affordance, workflow integration).

In addition, this thesis work contributes to advancing the OM literature’s understanding of analytic capability from Srinivasan and Swink (2018) in two ways. First, in addition to the examination of the complementary assets that organizations require to support the analytics capability, this work examines the underlying practices and processes that are used in the leveraging process of analytics capability. Thus, the findings from this thesis offer a holistic perspective on different ways that organizations can transform the information generated from their analytics capability through the three PoK steps, which can shed processual insights on the integration of the analytics capability into organizational routines and functioning. As suggested by Srinivasan and Swink (2018, pg. 186), this work also affirms that “analytics capability alone is not sufficient in improving operational performance”, and further contributes through identifying the various interactions between the different agents involved in the leveraging process and how they can afford routines that impact operational performances for organizations. Second, this thesis work contributes through the use of context to explain the leveraging process of organization’s analytics capability in the improvement of their operational performance. Understanding the context is important and should be carefully considered because there can be different forms of technology (e.g., BDA tools), agents involved, policy constraints, and standards depending on the context. This thesis work shows that, in the context of leveraging BDAC in healthcare, the organizations requires complementary functioning capabilities to create value from their analytics capability in the form of BDA-eFC, which has both dynamic and operational purposes.

Another theoretical contribution is in extending the current understanding of the relationship between BDA resources and BDAC. As noted in Chapter 2 of this thesis, the
general view in the BDAC literature is that BDA resources are the antecedents of BDAC (Brossard et al., 2022; Gupta and George, 2016). The notion that BDA resources lead to BDAC has been well established in the literature with both theoretical and empirical supports (Mikalef et al., 2018). A large part of the existing literature assumes that BDA resources and value is fully mediated by BDAC; however, our findings show that BDA resources may actually moderate the relationship between BDAC and value, as shown by the conditions and contingencies during the leveraging of BDA-based information. In the context of healthcare, this work contributes by introducing a possible role of BDA resources in moderating the impact of BDAC on value.

In addition, this work makes theoretical contributions through the application of KM-structuration middle-ranged theorization in understanding the mechanisms in which BDAC produces clinical and operational outcomes that lead to value within the healthcare context. Application of general theories such as the RBV have limited power in explaining the specific nature and interactions of the resources. Similarly, the KBV and the DCV can be useful in examining the types of knowledge and capabilities under a broad category, but do not provide the level of specificity that is needed to understand what might work for whom under what conditions. This thesis builds on the general theories and understandings in the existing literature in various domains to provide a middle-range theorization of the BDA-deployment gap phenomenon in the healthcare context, and in doing so, contributes to the existing body of work via exploration of possible mediators or moderators of the main relationship between BDAC and value. The PoK steps provide useful insights on the leveraging mechanisms of BDAC by breaking down the process into three separate but related steps. These processes show how different agents in the healthcare supply chain interact with other agents and structures to convert BDA-based information to enacted decisions and actions that can lead to
value. In contrast to the largely accepted linear pathway of BDAC to value, the KM-structuration theoretical perspective offers an iterative pathway towards value. Therefore, the development of BDAC and the leveraging process should be viewed as a recursive model as the outputs of the decisions and actions from BDA-enabled insights can impact not only the operational performance of the organization, but can also improve their existing BDAC.

Much of the research in management focuses on the organizational level capabilities in claiming that BDA applications can lead to competitive outcomes, yet, despite such claims, a large number of these initiatives have various purposes and performance measures. For example, the use of AI in predicting patient deterioration can provide incremental improvements to operations or innovative care delivery processes, where organizational-level vantage point may not be sufficient in understanding the reasons for a success or failure of BDA deployments. In contrast, this research examines functional-level changes that occur at the shop floor level and offers insights on how BDAC can lead to BDA-enabled work efforts with slight to no modifications to the current workflows (improved operational outcomes) or significant modifications to the current workflow (innovative operational outcomes). Thus, the dual-purpose nature of the BDA-eFC may provide insights on why some operational performance improvements are attained through automation, whereas others may come through augmentation.

5.1.2 Managerial Contribution

With many healthcare organizations now using health information technologies extensively in their daily operations, finding effective ways to leverage the exponentially growing data has become an important managerial concern. The abundance of healthcare data has only made BDA a focal point for many healthcare organizations as a way to harness the pool of potential opportunities to improve care quality and patient experience while reducing the cost of care.
for patients. As a result, a growing number of healthcare organizations have invested in BDA technologies and initiated various BDA deployments to develop the necessary BDAC, with hopes to generate knowledge that will help the organizations with strategic and operational decision-making and inform best practices. Investments in BDA continue to increase at a rapid speed, and the era of BDA is likely to change the healthcare industry. Despite the increasing investments made by healthcare organizations in deploying BDA initiatives, the number of successful deployments is relatively limited. This phenomenon of BDA deployment gap in healthcare is of significance due to the risks and potential financial losses that can come from failures, especially in the healthcare environment where budgetary and organizational resources are extremely constrained. Healthcare organizations and managers can maximize the value generated by their BDA investments by understanding the BDA value generation pathway; this offers extreme managerial value. This thesis reinforces the managerial challenges that are currently experienced by organizations investing in BDA in healthcare and provides insights on how value is created from BDAC.

When organizations invest in the development of BDAC, hospital managers tend to focus on the BDA resources (e.g., data assets, analytic technologies and techniques, human skills for analytics) and often overlook the holistic view of the value-generation process. This thesis provides a BDAC to value framework in the context of healthcare, which can help the managers of healthcare organizations understand how the information generated from BDA applications is converted into BDA-enabled insights and understanding that can inform patterns of enacted decisions and actions, thereby leading to improved workflows or innovative ways to deliver care to the patients. The comprehensive BDAC to value framework presented in this thesis further elaborates on the PoK steps during the knowledge conversion process, highlighting the interactions between different agents (e.g., physicians, data specialists, health
informaticists) and how BDA is incorporated into the daily workflows of the care providers. This can help inform the healthcare managers involved in various phases of BDA deployments with the functional level work efforts that are enabled by BDAC, which can provide a less abstract understanding of how value is generated from BDA investments. Furthermore, this thesis provides insights that can help healthcare organizations understand the challenges associated with the lack of successful value-generating migration of BDA models from data labs or third-party analytic service providers to in-practice environments by offering practice guidance on the operational efforts that enable the leveraging of BDAC. This in turn addresses the imitative-level BDA deployment gap for value generation in healthcare.

These findings strongly suggest that healthcare managers in organizations with BDAC to carefully assess and evaluate: (1) each of the PoK step in the BDAC value generation pathway to understand where at the functional level, the BDA deployment gap lies, (2) the interactions between the agents and the BDA technology within the organization, (3) their organizational abilities to support and drive the changes in the existing routines to integrate BDAC into them rather than forcing systematic changes through technology, and (4) the improved or innovated values that can be generated from the organization’s BDAC. Without these functional level BDA-enabled routines, the healthcare organization is likely not going to produce the operational performance improvements and create the intended values from the investments made to develop the BDAC. The detailed breakdown of the leveraging mechanisms of the BDAC can inform the healthcare managers of the processual and iterative work efforts that are required to effectively generate value from the BDA investments. This thesis offers managerial insights that demonstrate that the BDA implementations do not simply end with the implementation of the BDA tools and technology, but the healthcare managers should also strongly consider how the use of these tools are integrated into the daily workflows.
of its users, contribute to the development of new and improved organizational knowledge in the form of resources and processes, and properly manage them.

Healthcare organizations may face difficulties in identifying the specific areas they struggle with during the leveraging process of BDAC. For example, a healthcare organization may find greater success in converting BDA-based information into BDA-enabled insights but face challenges in converting BDA-enabled insights into operational understanding. The rules and resources identified in the PoK steps can help hospital managers identify the areas of challenge and prioritize the time and resources in improving certain parts of the value-generation process. Being aware of the gaps in the value-generation process can be of significant importance to healthcare organizations to minimize wasted resources and find methods to improve the knowledge conversion and application from BDA through practices such as hiring of liaisons, as seen in Figure 10 in the Chapter 4.

Lastly, the findings from this thesis demonstrate that the BDAC value-generation pathway is a recursive model and is inherently an iterative process. This indicates the need for organizations to be reminded that BDA deployments should not be viewed as “one-and-done” projects. To generate value from BDAC in a sustainable way, healthcare organizations need to continuously monitor, update, and make efforts to convert BDA-based information more efficiently and effectively into organizational knowledge embedded in functional-level routines that impact operational performance. This iterative value generation process requires a socio-technological consideration that considers how the users evolve with the use of BDA in the daily workflows.

5.2 Limitations

This section of the chapter will discuss several key limitations from the research efforts in this thesis. First, any type of literature review is subjected to various forms of biases related to
retrieval, availability, publications, inclusion/exclusion criteria, and biases related to the
tendencies of the reviewer. The SLR conducted in Chapter 3 attempted to avoid as much of the
aforementioned biases as possible through following some of the best practices of SLR in the
literature, but it is not fully bias-free. With respect to the range of dates of publications chosen
for the SLR, while it covers publications of peer reviewed scholarly journals from 2012 to
2021, it is not the most up to date list of literature because the SLR was conducted in 2021.
Instead of conducting another round of SLR, additional scoping review of the most recent
literature that examines BDAC and value in healthcare was conducted to stay up to date, and
this was added in section 4.2 of the multiple case study chapter. Based on the updated review
of the BDAC literature in healthcare and OM, the general findings from the SLR were
consistent.

Despite the large number of published papers on BDAC and value, the number of
returns with the healthcare term significantly reduced the total size of the literature samples. A
common issue that can arise from an SLR is from setting specific limitations to the context,
which can greatly reduce the generalizability of the findings from the SLR. The objective of
the thesis was to examine the BDA deployment gap in the healthcare industry; hence, the
research questions were carefully chosen and framed to reflect this. This in turn has resulted in
including the healthcare context as part of the inclusion/exclusion criteria.

The SLR in this thesis uses eight different electronic databases: INFORMS/ABI,
EBSCO-Business Source Complete and Academic Search Ultimate, SAGE, Wiley, Emerald
Insight-Business Management & Economic Book series, Taylor & Francis, SCOPUS, and Web
of Science. Although eight databases would likely be an acceptable number of databases to
cover an adequate number of documents for the study, it is true that if more databases had been
utilized, the chances of identifying more relevant papers could have been increased, thus further increasing the study’s accuracy.

Some limitations were also found in the multiple case study. One of the main limitations was to do with an external factor, the COVID19 pandemic. There were several implications of the pandemic on the multiple case study. First, due to the restrictions placed, the interviews could not be conducted in-person. Instead, the bulk of the interviews were performed on a video conferencing platform. Video conferencing interviews can impose restrictions on the researcher’s ability to assess the informants’ environment, which can provide useful contextual data to inform the content of the interviews during the data analysis phase. In addition, it is difficult to observe the entire range of body language and different forms of nonverbal communication when the informants’ image is often shown only from the waist up. However, the use of video conferencing tools has been increasing for qualitative data collection (Lobe and Morgan, 2021), and there were also benefits such as scheduling flexibility for informants with extremely busy schedules. Furthermore, the recorded interviews added tremendous value by allowing the researcher to replay the conversations during the data analysis phase. Some of these shortcomings were addressed through site visits that occurred after the pandemic restrictions lifted.

In the pursuit of feasibility and affordability of data collection, all of the healthcare organizations selected for the multiple case study were located within the province of Ontario, Canada. Healthcare systems can vary from country to country; even within the same country, systems can vary depending on the state or province in which the organization is located. As a result, the findings from the multiple case study may not be fully generalizable to healthcare organizations in different countries or regions. For example, Canada has a national health insurance program (NHI), and the health insurance coverage is universal and follows a single
payer system, whereas in the US, there is no single nationwide system of health insurance and the health insurance is purchased from the private marketplace or funded by the government to certain subsets of groups. The healthcare organizations that are for profit may have different organizational goals for using BDA compared to not-for-profit healthcare organizations. Although, the healthcare professionals, regardless of their regions, take the utmost level of seriousness in valuing the patients’ health as the higher priority, the intended purpose and values from BDA deployments may vary depending on the type of healthcare system that the organization belongs to. Furthermore, all of the healthcare organizations in this study follow a tripartite structure, which means that one of the main uses of the BDAC is for research purposes. Therefore, the samples from the multiple case study may not reflect the organizations that do not consider innovation or research as one of the strategic objectives.

5.3 Future Research

As previously discussed in Chapter 1 of this thesis, a large part of the OM research in BDA focuses on the BDA techniques and models; therefore, research in BDAC is still a relatively new area in healthcare OM. This means that there are many avenues for practically relevant and interesting research questions to be addressed. This section of the chapter highlights future research opportunities that emerged from the findings of the thesis.

5.3.1 Value Capture from BDAC

While the focus of the multiple case study was on examining BDA-based value creation in the value pathway from BDAC to value in healthcare, as discussed in Chapter 2, BDAC enables the opportunity for value creation but does not directly yield value delivery and capture. The multiple case study empirically demonstrates that the value delivery occurs through the workings of BDA-eFC. Therefore, whether the enabled transformation of the current rules and resources through the use of technology-in-practice (e.g., BDA applications, BDA-based
information) leads to realization of value in the form of overall financial performance has not been tested in this study. Quantifying financial impact was not the objective of the multiple case study, and measuring financial implications of the improved service offerings and the servicing efforts can be particularly challenging in the healthcare setting. The difficulties in measuring the financial impact were observed in the healthcare organizations as well. Questions related to the challenges in measuring the cost of reduction in mortality, and it is difficult to demonstrate that it was due to the BDA implementations. The answer to this question came from an informant from another healthcare organization, where they were attempting to measure financial impacts of BDAC through proxy measures to understand and quantify the values captured from BDAC. Future studies could take an approach that focuses on how organizations actually capture the value created through BDAC in the form of measurable financial impacts or productivity (e.g., reduction in physician time spent on each patient) outcomes.

5.3.2 Factors that Impact the Enacted Decisions and Actions by End-users

As discussed in the findings section of the multiple case study, one of the interesting insights that emerged was that even with BDA applications having high accuracy and performance, some of the end-users (e.g., physicians) continue to go through the PoK steps but fail to enact their decisions and actions based on information from BDAC, instead, reverting to what has been comfortable in the past. Within the healthcare supply chain, the BDA-based value created in the upstream supply chain may not be captured in the downstream supply chain by the patients if the care providers fail to enact the BDA-enabled decisions and actions. This directly relates to the last of the PoK steps findings in this thesis. In addition to the technological factors related to the capabilities of the BDA applications, social factors, such as trust and disturbances to the workflows of the end-users, can also significantly impact whether the BDA-enabled
knowledge generated is enacted. This finding raises noteworthy questions: (1) what factors influence the care providers (end-users) to take actions on the BDA-enabled knowledge, and (2) how is this sustained? To answer these questions, a quantitative research design with a narrower scope that examines a particular BDA application (e.g., AI predictive analytics tool for certain symptoms) and its use with a specific agent group (e.g., physicians) is likely required.

5.3.3 Application of BDAC to Value Framework to Specific BDA Forms and Types

Although the research adopts a multiple case study approach to identify a broad set of BDA deployments in examining the value generation pathway between BDAC and value, it may be possible that each type of BDA deployment entails different configurations of the enabled functioning capabilities and PoK steps. To answer the research questions proposed in this thesis, it was necessary to group the BDA applications under the larger umbrella of BDAC, which resulted in the general BDAC to value framework that can be applied in various settings in healthcare. As the findings suggest, different forms and types of BDA applications may moderate how BDAC leads to value.

A commonly discussed theme that emanated from the qualitative data was the use of AI and augmented decision-making in healthcare. More healthcare organizations are using algorithms to design AI-based tools that can learn. This added layer of learning can enable or constrain the learnings that occur in the human agents. As the findings suggest, information from the predictive analytics tool can afford the experienced care providers with information that reminds them of their prior knowledge, but it can also cause the novice care providers not to learn because there is no longer a need when the knowledge is provided by the technology. This, in turn, can diminish the critical thinking skills that are required by the healthcare professionals and limit the learning that takes place for the human agents. As an extension of
the thesis efforts that transpired to the identification of the BDA-eFC in the BDAC to value framework, future studies should be taken to test the applicability of this framework for specific BDA applications.
Chapter 6

6. Reference & Appendices


Coatney, K., 2018. Big data analytics capabilities, the business value of information technology, and healthcare organizations: the need for consensus in evidence-based medical practices. American Journal of Medical Research 5, 28–33.


https://doi.org/10.1371/journal.pmed.1000097


A. Systematic Literature Review Keyword Search Command

**Big data analytics capabilities:**
Full text: ("big data" OR "big data analytic") AND ("big data analytics capabilities" OR "big data analytics capability") AND ("value" OR "performance" OR "competitive advantage" OR "business value" OR "outcome") AND ("healthcare" OR "health care" OR "medicine" OR "health" OR "medical" OR "care")

Abstract and/or title: ab,ti("big data" OR "big data analytic") AND ab,ti("big data analytics capabilities" OR "big data analytics capability") AND ab,ti("value" OR "performance" OR "competitive advantage" OR "business value" OR "outcome") AND ab,ti("healthcare" OR "health care" OR "medicine" OR "health" OR "medical" OR "care")

**Dynamic capabilities:**
Full text: ("big data" OR "big data analytic") AND ("dynamic capabilities" OR "dynamic capability" OR “organizational capability” OR “organizational capabilities”) AND ("value" OR "performance" OR "competitive advantage" OR "business value" OR "outcome") AND ("healthcare" OR "health care" OR "medicine" OR "health" OR "medical" OR "care")

Abstract and/or title: ab,ti("big data" OR "big data analytic") AND ab,ti("dynamic capabilities" OR "dynamic capability" OR “organizational capability” OR “organizational capabilities”) AND ab,ti("value" OR "performance" OR "competitive advantage" OR "business value" OR "outcome") AND ab,ti("healthcare" OR "health care" OR "medicine" OR "health" OR "medical" OR "care")

**Operational capabilities**
Full text: ("big data" OR "big data analytic") AND ("operational capabilities" OR "operational capability" OR “routine” OR “routines”) AND ("value" OR "performance" OR "competitive advantage" OR "business value" OR "outcome") AND ("healthcare" OR "health care" OR "medicine" OR "health" OR "medical" OR "care")

Abstract and/or title: ab,ti("big data" OR "big data analytic") AND ab,ti("operational capabilities" OR "operational capability" OR “routine” OR “routines”) AND ab,ti("value" OR "performance" OR "competitive advantage" OR "business value" OR "outcome") AND ab,ti("healthcare" OR "health care" OR "medicine" OR "health" OR "medical" OR "care")

**Combination of all three**
Full text: ("big data" OR "big data analytic") AND ("big data analytics capabilities" OR "big data analytics capability" OR "dynamic capabilities" OR "dynamic capability" OR “organizational capability” OR “organizational capabilities”) AND ("value" OR "performance" OR "competitive advantage" OR "business value" OR "outcome") AND ("healthcare" OR "health care" OR "medicine" OR "health" OR "medical" OR "care")

Abstract and/or title: ab,ti("big data" OR "big data analytic") AND ab,ti("big data analytics capabilities" OR "big data analytics capability" OR "dynamic capabilities" OR "dynamic capability" OR “organizational capability” OR “organizational capabilities” OR "operational capabilities" OR "operational capability" OR “routine” OR “routines") AND ab,ti("value" OR
"performance" OR "competitive advantage" OR "business value" OR "outcome") AND ab,ti("healthcare" OR "health care" OR "medicine" OR "health" OR "medical" OR "care")
B. Multiple Case Study Research Protocol

Overview of the cases

- Description of the organization’s missions and values in the implementation of BDA
- Description of the informant(s) role with the organization and previous experiences
- Description of the different types, numbers, and purposes of the BDA deployments, and the gaps experienced by the organization
  - Highlighting the big data analytics capabilities that the organizations possess, and the challenges faced by in leveraging the capabilities
- Description of the key impact factors or values of BDA on healthcare delivery service
  - Different forms of the intended values to be generated from BDA
  - Different forms of the realized values generated from BDA
- Details on the organization’s operational practices involved in utilizing BDA tools
  - Pre-existing healthcare practices
  - Changes that occurred in the existing operational practices with the BDA initiatives: new routines, modified routines
  - Processes involved in using the information from BDA applications to inform decision-making
  - Challenges faced during the systematic implementation and changes in practices
  - Identification of the end-users of the BDA tools
  - Enhanced practices through the BDA deployments
- Description of the effectiveness or performance of the BDA initiatives
  - Performance improvements
  - Values for the organizations
  - Values for the patients
  - Financial values
  - Functional values
  - Methods of evaluations of the performance
- Supplementary attachments provided by the informants and organizations:
  - Third-party electronic healthcare record provider information
  - Blogs and articles of organizations’ success stories of BDA deployments
  - Diagram of information governance structure if possible
  - List of interviewees with contact information

Sample interview questions

The responsibility and the role of the interviewee at the organization and their experience with big data analytics.

1. Please describe your responsibility and the role in the organization, and the years of experience you had with big data analytics in general and in the healthcare industry specifically.
2. As you are helping your clients with big data analytics projects, what is the nature of your involvement?
Defining the constructs: big data, big data analytics, big data analytics capability and operational capability, and service functionality.

1. Other than the three major characteristics of big data (volume, variety, and velocity), do you believe that there are other characteristics that are relevant in healthcare big data?
2. From your experience, what are the major capabilities (resources and skills) required to leverage the information gathered from healthcare big data?
3. When healthcare organizations reach out for expert opinions on healthcare big data analytics, what are they seeking to achieve (what are the main objectives from healthcare organizations in leveraging big data analytics)?

The BDA initiative in operation and its impact on healthcare delivery service.

1. Please describe the BDA initiative in detail, including the healthcare organization(s) involved, the project, and deployment of technologies.
2. How do these BDA practices start? Do the healthcare organizations realize the gaps and inefficiencies in the current healthcare system or do the healthcare data analytics companies reach out to them first?
3. Please describe the process of extracting valuable/useful information for healthcare big data, and how value is generated from using big data?
4. In what ways do you believe that the practice has changed or enhanced the existing healthcare service practices (functionally)?

Evaluations and challenges of the BDA practices for healthcare organizations.

1. What is the design for evaluating the practice, and who is doing the evaluation?
2. What are the outcome measures being used, and what outcomes are healthcare organizations most interested in?
3. What are the biggest challenges that prevent healthcare organizations from efficiently and effectively leveraging big data analytics to generate business value?

Additional Questions Based on Roles

Questions for Executives (Chief Operations Officer, Chief Information Officer, or Executive Project Manager)

1. How would you describe the value of big data analytics for your healthcare organization? What would you say is the greatest value of big data analytics for your healthcare organization and the healthcare industry as a whole?
2. Do you believe that your organization has successfully implemented big data analytics and leveraged it to generate value for your healthcare organization, and were there any major challenges that were faced in the process?
3. How does your organization transform data into useful information that can be used to generate value for the organization?
4. How does your organization transform information from data analytics to knowledge and insights that can be leveraged to generate operational value?
5. What are the essential operational capabilities that your healthcare organization would require to leverage big data analytics effectively and efficiently?

6. Could you describe the general pathway of the value generation process of big data in your healthcare organization? What are the operational benefits of using big data analytics in healthcare organizations?

Questions for Data Analysts or Specialists

1. Could you describe your role in the process of value creation from big data analytics in your organization?
2. How would you describe the value of big data analytics for healthcare organizations, and what would be the greatest value of big data analytics for your healthcare organization and the industry as a whole?
3. Have the big data analytics deployments been able to generate the values that you have set out to attain with them?

Questions for Clinicians or other care providers

1. Could you describe your role in the development and use of the big data analytics deployments in your organization?
2. How often do you interact with the analytic tools daily?
3. Are there any instances where you have good analytic tools and capability, but these do not yield the intended results when implemented?
4. Did having good analytic tools and data help you in improving patient outcome, experience, or cost reduction? If yes, which did it help in improving, and if not, what else did you need?
5. What are the outcomes that you were able to get from using the information from big data analytics deployments?
Curriculum Vitae
Hyunmin (Dan) Shin

EDUCATION

Expected 2023  
**PhD, Business Administration, Operations Management**  
Ivey Business School, Western University

2016  
**Masters of Environment and Sustainability**  
Western University

2014  
**Bachelor of Science (with Honours)**  
McMaster University

ACADEMIC EXPERIENCE

January 2020 – April 2022  
**Lecturer**  
Western University  
Operations Management – MOS 3330 (Fall, Winter)  
- Taught two sections per each term, utilizing lecture-based teaching for both online and in-class as needed; delivered lectures for a full course; managed grading and evaluations.  
- Course entailed two midterms, presentation, and final exam.  
Teaching evaluation: 6.3/7

January 2023 – April 2023  
**Limited Duties Faculty**  
Ivey Business School, Western University  
Operations Management – Honors Business Admin. Core (Winter)  
- Will be teaching one section, utilizing case-based teaching in-class and responsible for delivering lectures for a full course, and managing grading and evaluations.

RESEARCH

Papers
- Currently going through final edits.

- Data collection and analysis complete.

- Project started with multiple hospitals, specifically with the nursing department.  
- Employing experimental design method.
**Invited Conference Presentations (*presenter)**


**TEACHING CASES**


**HONORS AND AWARDS**

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<tr>
<td>2022</td>
<td>Summer Term Graduate Bursary</td>
<td>Ivey Business School, Western University</td>
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<td>C.B. (Bud) Johnson Ontario Graduate Scholarship</td>
<td>Ivey Business School, Western University &amp; Province of Ontario</td>
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<tr>
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<td>Brock Scholarship</td>
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</table>
2017 – 2020  **Plan for Excellence Doctoral Fellowship**  
Ivey Business School, Western University

2015 – 2016  **Fallona Family Interdisciplinary Service Ontario Graduate Scholarship**  
Western University & Province of Ontario

**OTHER TEACHING & RESEARCH EXPERIENCE**

2018 – 2021  Grading Assistant  
Ivey Business School, Western University  
- Worked with Clarence Borja (2018, 2019), Dr. Deishin Lee (2019), Dr. Jury Gualandris (2020, 2021), and was responsible for grading HBA Operations midterm 3304 and final exam.

2017  Research Assistant  
Ivey Business School, Western University  
- Worked with Dr. Stephan Vachon on creating summary for COSIA (Canada’s Oil Sands Innovation Alliance) and the related projects.

**SERVICE**

**Ad-hoc Reviewer**  
Decision Sciences Annual Meeting, 2018  
Asian Journal of Sustainability and Social Responsibility

**Committee Member**  
PhD Association – VP Social (2019/2020)  
PhD Mentor/Mentee for Operations Management (2019/2020)  
Society of Graduate Studies Council (2018/2019)

**Professional Organization Member**  
Academy of Management  
Decision Sciences Institute  
Production and Operations Management Society

**TECHNICAL SKILLS**

Programming Languages  
- R, Python

Statistical Data Analytics  
- SPSS, STATA, Mplus, Excel

Qualitative Data Analysis  
- NVivo

**PROFESSIONAL DEVELOPMENT**

October 2021  Intermediate R Workshop  
- 4-hour workshop, working through example analyses from starting to finish.  
- Included data cleaning, descriptive statistics, different types of statistical modelling, and presentation
April 2019  Advanced Teaching Program (ATP) Course
- Teaching support center 5-day training session (4 hours per day) to educate participants regarding practical skills, fair student assessment, student engagement, and classroom diversity
- Included two mini-teaching sessions, personal feedback, and capstone project where you design and develop course syllabus

NOTEABLE COURSES TAKEN

April 2019  Big Data Analytics in Business, MBA Course
Ivey Business School, Western University
- Building on analytical/statistical framework and skills for making decisions with analytics using R
- Topics covered were analytics visualization, regression-based forecasting, CART analysis, logistic regression, LASSO regression, neural networks, k-nearest neighbor, and cluster analysis

January 2019  Identification of Causal Effects, PhD Course
Ivey Business School, Western University
- Introduction of advanced econometric and statistical methods used to analyze applied research questions in management using STATA and R
- Topics covered were instrumental variables, regression discontinuity designs, limited depend variable models, statistical inference, natural experiments and identification

January 2019  Research Design and Statistical Modelling, PhD Course
Ivey Business School, Western University
- Covered main univariate and multivariate statistical modelling procedures in psychology and other research areas using SPSS, R, and Mplus
- Topics covered were simple and advanced models in analysis of variance, multiple regression techniques, and multi-level modelling

April 2018  Special Topics in Structural Equation Modelling, PhD Course
Ivey Business School, Western University
- Developing data analysis skills using SEM and multi-level modelling techniques using SPSS and Mplus
- Topics covered were measurement models, path analysis, latent factor modelling, latent growth models, and multi-level models