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How Healthcare Big Data Analytics Information Asymmetry Influences Organizational Design Absorptive Choices

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Abstract

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MBA, Concordia University, 2017

BS, Francis Marion University, 1989

Dissertation Submitted in Partial Fulfillment

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Abstract

Although the relationship between big data analytics (BDA) organizational, firm, and financial performance is well supported, little attention has been paid in extant research to exploring the organizational design issues resulting from information asymmetry caused by BDA; in particular, organizational absorptive choices that include acquisitions, mergers, reorganization, executive changes, or board of director adjustments. The purpose of this qualitative single case study within a U.S. hospital was to explore the conditions and circumstances that influence absorptive organizational design choices of hospital administration. The theoretical base of this study is Pfeffer and Salancik's resource dependence theory (RDT). Logic model data analysis approach was conducted on primary data attained from semistructured interviews of 12 volunteers of hospital administration and secondary data from grey literature. The findings of this study suggest resource dependence theory activities of executive changes and intra-organizational structural changes moderate information asymmetry. Communication was the major theme, while properly formed BDA questions, prospective reimbursement models, evolving BDA demands, intellectual capacity gap, and operational complexity were minor themes that influenced organizational design decisions. The practical implications emphasize communication among multidisciplinary groups and boundary-spanning organizational design strategies to moderate information asymmetry. Lastly, the positive social change implication may be the increased BDA adoption in hospital administration from the improved communication among individual actors of multidisciplinary BDA groups.

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Dedication

I would like to dedicate this dissertation to my wife, Deborah. Thank you for your unwavering support and patience during this journey.

Acknowledgments

I want to thank several people who made this study possible. First, my family, their support has been tremendous. Second, I want to thank my dissertation committee, Dr. Aridaman Jain (Chair), Dr. Kimberly Anthony, and Dr. Robert Levasseur. Their guidance and encouragement have been immeasurable. Finally, I would also like to thank the interview volunteers who contributed to this investigation. Thank you for your time and willingness to assist me in completing my dream and study.

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Chapter 1: Introduction to the Study

The concept of *big data analytics* (BDA) has emerged in management research as a technical capability that increases the speed of the decision-making process by parsing vast and diverse troves of digital information to cultivate actionable information (Fiorini et al., 2018). High information asymmetry is surfacing as a new challenge for organizational leadership implementing BDA. *Information asymmetry* is the condition in which BDA experts have better and more actionable information than traditional executive leadership that has historically relied on intuition and experience to inform their decision-making process (Galbraith, 2014). The challenge of information asymmetry is amplified for hospital administration as they are also burdened with managing highly regulated patient data (Urbinati et al., 2019). Given the embryonic nature of current BDA solutions, these experts are typically external to the organization or relegated to information technology (IT) groups (Wang & Byrd, 2017). In this study, I explored the organizational design choices of hospital administration faced with the information asymmetry BDA implementation. More specifically, I sought to understand the conditions and circumstances that influence their absorptive organizational design choices, such as corporate mergers, executive administration changes, board of director (BOD) adjustments, or organization structural changes.

The prior paragraph permits a deeper discussion of the background of this study. The background section presents a summation of the literature related to BDA along with a description of the research gap in management scholarship. The remainder of Chapter 1 covers the following topics: the purpose of the study, research question, nature of the study, theoretical foundation, definition of critical terms, scope, limitations, and the significance of the study to management theory, business practice, and social change.

Background of the Study

Healthcare is becoming more data-centric (Mehta et al., 2020) as the delivery, diagnosis, and treatment become more evidence-based and personalized (Schaefer et al., 2019). This new healthcare paradigm forces healthcare administration to rethink existing organizational structures to buttress their business models. Capitalizing on BDA throughout the healthcare ecosystem requires cooperation and collaborations not seen before (Kim & Park, 2017). Moreover, the capability to capture and store structured and unstructured digital health data referred to as *big data*, has outpaced the capacity to analyze and derive actionable information (Prosperi et al., 2018). *BDA*, which is the integration and processing of heterogeneous digital data with specialized tools to discover new relationships and discover actionable insights (Ristevski & Chen, 2018), has the potential to positively impact patient care as well as lower the cost of care (Milenković et al., 2019; Raghupathi & Raghupathi, 2014; Wetering, 2019). Other vital benefits include improved decision-making, greater realization of strategic initiatives, improved patient relations, and better risk management (Muruganantham et al., 2019). As for healthcare, BDA could radically change its operational paradigm, potentially linking every aspect of care to clinical outcomes. This linkage could offer intelligence and transparency in managing patient care, operating costs, and outcomes that do not exist today (Kim & Park, 2017). Regardless of the benefits, the healthcare BDA adoption rate falls well short of other industries.

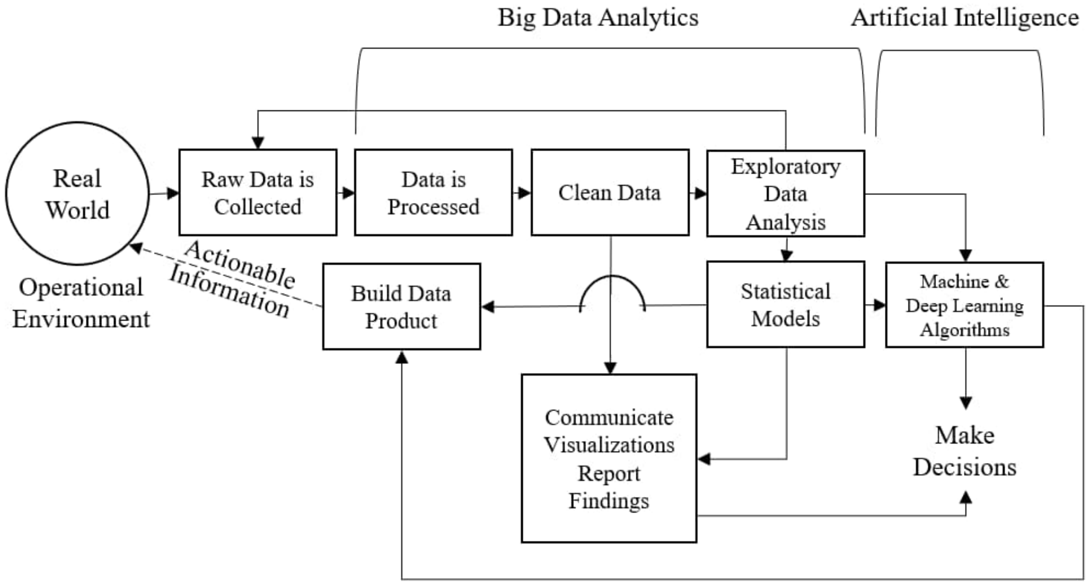
Reducing healthcare costs has never been more imperative, as the United States spends far more on healthcare per capita than other countries with similar life expectancies (Bidgoli, 2018). Healthcare costs in the United States represented 17.9% of the gross domestic product (GDP) in 2017 and are estimated to be 19.4% by 2027 (Zeadally et al., 2019). An estimated $191 billion to $282 billion of these costs are waste due to high transaction costs and inefficient healthcare operational processes (Shrank et al., 2019). Research has suggested that BDA can improve operational performance in a supply chain setting (Dubey et al., 2020). Furthermore, Christensen et al. (2006) argued that the new healthcare paradigm needs a technological sea change to mitigate rising costs and stimulate fundamental social change. BDA may be the disruptive innovation needed to meet the challenges faced by healthcare administration.

Data Process Continuum

The reasons for the use of BDA in healthcare outlined above permit now a necessary delineation between BDA and artificial intelligence (AI) algorithms before outlining the relevant BDA research. Scholarly authors often conflate the terms BDA and AI. Figure 1 is adapted from the work of O'Neil and Schutt (2013) and represents a logical relationship between BDA and AI. The continuum begins with collecting raw data from real-world operational environments such as healthcare, as was the case with this study. Then, the data are processed using specialized tools by BDA experts to aid in decision-making processes. Finally, the continuum concludes with AI automating the tasks. In short, the process of BDA precedes the development of AI algorithms.

Figure 1

Data Process Continuum



Note: Adapted from *Doing Data Science: Straight Talk from the Frontline*, by C. O'Neil and R. Schutt, 2013. Copyright 2013 by Cathy O'Neil and Rachel Schutt.

Organizational Actors

According to Y. Wang and Byrd (2017), healthcare units are likely to derive actionable information from utilizing BDA, which indirectly influences the decision-making process through the absorptive capacity of organizational actors. Their study results support the proposition that using BDA effectively may positively impact hospital operational performance. These findings are essential to this study as they suggest that hospital administration may benefit from including organizational actors with a BDA managerial orientation.

Cabrera-Sanchez and Villarejo-Ramos (2019) showed that proper organizational infrastructure outweighed the technological barriers of implementing BDA in a cross-industrial context. Furthermore, their study results showed that future user expectations of BDA were higher and that current users of BDA were skeptical. This study further suggested that organizational actors with a BDA managerial orientation are associated with the effective use of BDA.

Y. Wang and Hajli (2017) constructed a business value model in healthcare BDA through the lens of the resource-based view (RBV) and capability building theory. The business model presents a map of BDA capabilities to business value pathways for healthcare organizations. The results of Y. Wang and Hajli's research are relevant for two reasons. First, the study highlights the complexities of creating business value from healthcare BDA implementations, particularly data privacy and security. Second, the research emphasizes the need for new capabilities. The findings of this study suggest that unique circumstances and organizational conditions play a role in the effective use of BDA.

Caesarius and Hohenthal (2018) showed how antecedent characteristics of leadership incumbents in a cross-industry Scandinavian context could influence BDA adoption decisions. Their findings suggest that leaders with a BDA managerial orientation can influence BDA adoption decisions. These findings are related to the present study as they indicate that incumbent leadership may influence an organization to adopt BDA within the operational paradigm.

Organizational Design

Velthoven et al. (2019) found that intra-healthcare organizational partnerships, including competitive organizations, positively impacted BDA adoption. The findings in their study suggest that hospitals lacking perceived attributes of innovative BDA capabilities should institute mechanisms that buttress their capabilities through partnerships. Along the line of the Velthoven partnership study, the results of this study concerning the mitigation of information asymmetry through organizational design may lend credence to the applicability of resource dependence theory (RDT) to the phenomena of information asymmetry.

Nam et al. (2019) showed that organizational factors such as data-related technological characteristics influenced BDA adoption in a Korean cross-industry context for all stages of the adoption process. In contrast, the environmental aspect of competition influenced only the initiation stage. Thus, the results of their study suggest that both organizational and environmental design conditions affect the use of BDA. Similarly, Lai et al. (2018) showed that perceived benefits and top-level management support could influence BDA adoption intention in a general supply-chain context. The results of their study suggest there are organizational conditions or leadership circumstances that affect BDA use decisions.

According to Y. Wang, Kung, and Byrd (2018), five essential BDA capabilities can facilitate a path to the business value of BDA. Using content analysis of 26 big data implementation cases in healthcare, the authors identified five BDA capabilities: identify patterns of care, process unstructured data, decision support, predictive (results visualizations), and traceability. The findings of this study suggest hospital administration lacking these embedded organizational capabilities may need to acquire or absorb resources.

Ristevski and Chen (2018) critically reviewed the healthcare big data literature and identified the challenges of implementing BDA. The authors highlight big data privacy and security as the underlying barriers to effective BDA. Further, the authors also suggest promising open-source software solutions that may mitigate the obstacles. The results of this study are related to this study as they highlight that the effective use of BDA may also require hospital leadership to consider new technological and managerial capabilities.

Y. Wang, Kung, et al. (2018) developed a conceptual model of BDA adoption through a critical literature process. The authors tested the model using 33 qualitative case descriptions, revealing three essential links between digital organizational transformations to BDA. The first dimension is that evidence-based medicine may lead to business value. Second, that unity in practices based on decision-support capabilities can be derived from BDA. Lastly, there is a link between operational efficiencies and the effective use of BDA-based decision-making capability. The results of this study emphasize several conditions that hospital administration should consider as essential to the effective use of BDA.

The motivation for studying BDA and information asymmetry in healthcare is rooted in the lack of widespread effective use of BDA in healthcare, despite its proliferation in other industries and sectors of the economy (Grover et al., 2018). Further highlighting the disparity, healthcare industry manufacturers are devoting more significant percentages of resources, technologies, and products and services focused on the topic of BDA (Shah et al., 2019). These trends suggest that factors or phenomena unique to healthcare may inhibit BDA adoption and realize business value from its implementation.

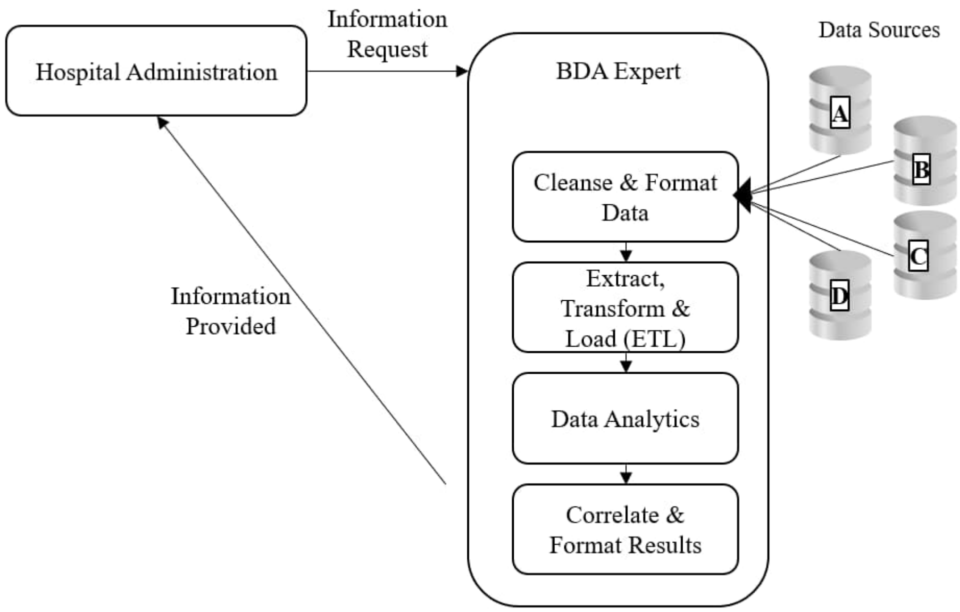
Problem Statement

The information asymmetry caused by BDA implementations creates organizational design issues for hospital administration (Bergh et al., 2019; Wehrens et al., 2020). Healthcare BDA is an embryonic curation capability in which actionable information is derived from heterogeneous digital healthcare data sources using specialized tools (Ristevski & Chen, 2018; Surbakti et al., 2020). At the same time, information asymmetry is when one party has more or better information than another (Bergh et al., 2019). Thus, BDA in healthcare creates high information asymmetry between hospital administration that needs data-driven actionable information and the BDA experts that can safely and securely curate large amounts of digital data. Figure 2 illustrates the process transaction between hospital administration and BDA experts. The prevalence of information asymmetry is evidenced in a 2015 survey of 15% of large hospital BDA experts, revealing that most organizational designs centralize BDA tasks and management with IT rather than clinical business experts (Wang & Hajli, 2017). Figure 3 illustrates how information asymmetry increases as the organizational separation between hospital administration and BDA experts grow. More recently, a survey of Big Data executives across industries showed that a growing number are beginning to hire

BDA experts from within their organizations (New Vantage Partners, 2021). Scholars suggest the highly regulated nature of patient data and security concerns are unique issues to healthcare's effective use of BDA (Wehrens et al., 2020). As such, hospital administration must consider organizational designs that balance the tendency to reduce information asymmetry against the requirements of patient data security.

Figure 2

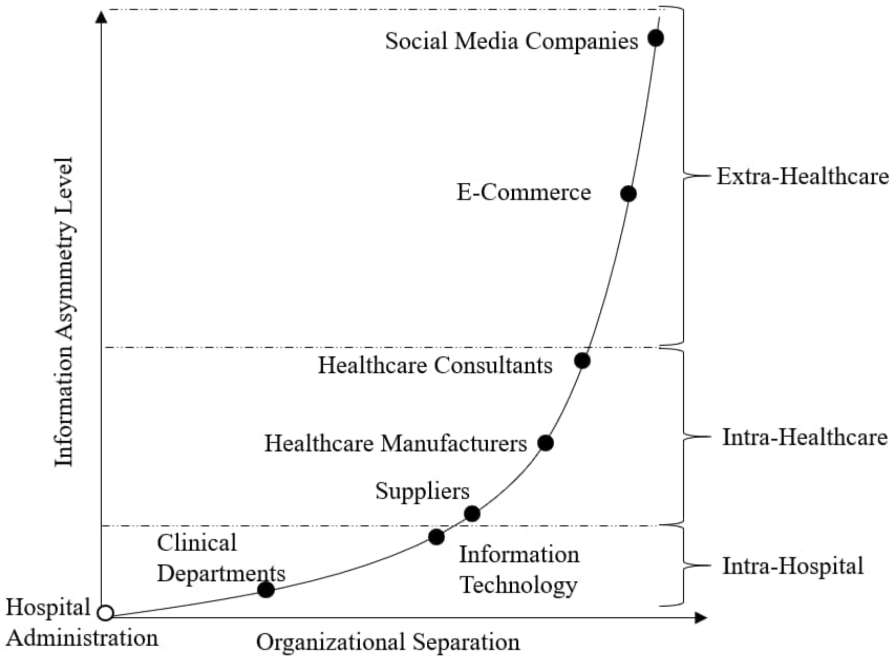
BDA Process Transaction



Note: Adapted from "Data Analytics: The Big Data Analytics Process (BDAP) Architecture," by J. Crowder, J Carbone, and S. Friess, 2020, *Artificial Psychology*. Copyright 2020 by Springer Cham.

Figure 3

Logical Representation of Information Asymmetry in Healthcare



BDA strategic alliance approaches (He et al., 2020) and collaborative organizational strategies (Akter et al., 2016) are well-studied in healthcare. However, there is no research on the costly absorptive organizational design choices hospital administration faces in high information asymmetric environments (Al-Badi et al., 2018; Bergh et al., 2019; Mandlik & Kadirov, 2018). Therefore, the specific research problem this study addressed was a lack of understanding of the conditions and circumstances that influence hospital administration to make organizational absorptive choices to reduce the information asymmetry from BDA.

Purpose of the Study

The purpose of this qualitative single case study was to explore the circumstances and conditions that influence hospital administration organizational design absorptive choices to reduce information asymmetry caused by BDA. Using the lens of RDT, the focus of this study was on how hospital top management and administrators of embedded units (e.g., IT, Clinical, Procurement, Logistics) absorb the resources and capabilities to mitigate the information asymmetry from BDA. Hospital *resources* are the tangible and intangible assets at this stage, whereas *capabilities* are the entrenched non-transferable competencies needed to implement the hospital's BDA strategy. The data from this study may contribute to new knowledge and insights into how hospital administration makes costly absorptive organizational design choices. The findings may also promote social change by improving BDA adoption, which scholars have shown improves hospital performance.

Research Question

How do the circumstances and conditions of information asymmetry caused by BDA influence the organizational design choices of hospital administration?

Theoretical Foundation

Clearly stating a theoretical background provides a sufficient basis for this research and binds the above research question into current academic literature. The theory that grounds this study is Pfeffer and Salancik's (1978) RDT, which suggests that organizations will undertake actions to reduce uncertainty and reliance on external resources to shore up their business model. These actions include mergers and acquisitions (M&A), joint or intra-organizational ventures, changes in the BOD, political activities (including regulatory actions), and executive change actions.

The connection between the research problem and the nature of this study is Pfeffer and Salancik's theory, which has been used extensively in organizational design and information asymmetry research (Bergh et al., 2019). The underlying argument of RDT is that organizations survive on a network of interdependencies with both internal subgroups and external organizations. Prospering in an interlinked environment requires control over a finite supply of vital resources (Hillman et al., 2009). According to Zeng and Glaister (2018), firms must acquire, house, process, and exploit resources to realize value. Following this logic, the specific connection of this study to RDT is that BDA competence is the vital resource that hospital administration will seek to control by reducing the organizational separation, thereby reducing information asymmetries.

Nature of the Study

The qualitative research tradition was best suited to address the research question of this study, particularly when current circumstances, as in this study in which little a priori research exists (Singh et al., 2019). Specifically, the approach is a single critical case study with multiple embedded units design (Yin, 2018). As mentioned earlier, the purpose of this case study was to develop a comprehensive understanding of the real-life conditions and circumstances that influence the absorptive organizational design choices of hospital administration confronted with high information asymmetry environment (Eisenhardt, 1989). Case selection is an essential consideration in qualitative research, especially given the nascence of the phenomena and the fact that the results of this case study ultimately rely on the selection criteria (Herron & Quinn, 2016). I will present a detailed argument for a single critical case study approach in Chapter 3.

Borrowing from Y. Wang, Kung, and Byrd (2018), case selection criteria included (a) that the case organization presents an actual BDA implementation platform or initiative and (b) that a change in organizational design was implemented by leadership. Case selection was conducted from a population of online and gray literature published use cases. To support transferability, I have selected a single critical case approach that includes multiple embedded interrelated functional groups. The method of multiple embedded interrelated functional groups is based on Hopkins and Hawking (2018), investigating the use of BDA in the supply chain to enhance driver safety and lower operating costs.

Borrowing from Easton (2010) and Yin (2018) I gathered primary and secondary data to generate contextual conditions regarding real-world cases from ongoing and historical data sources. Data analysis was performed using a logic model analytic approach (Funnell & Rogers, 2011). The logic model analytical technique is compatible with this study. Furthermore, the process is designed to match observed events to the theoretically predicted events of this study's RDT framework (Yin, 2018).

Definitions

According to Hodgson (2019) some domains of social science do not develop an adequate level of definitional terms, yet proper definitions are vital for proper communication among scientists. Furthermore, the appropriate definition includes the necessary and sufficient features of terms and concepts to afford clear classification decisions (Pothos & Hahn, 2000). The following definitions identify the necessary and sufficient features of key terms used in the study.

Absorptive capacity: "Organizations' ability to absorb intangible resources (such as knowledge, know-how and expertise) and transform them into unique dynamic capabilities, which are not easily imitated by competitors" (Siachou et al., 2021, p. 412).

Artificial intelligence: Any intelligence demonstrated by a machine that leads to an optimal or suboptimal solution given a specific problem (Aboshiha et al., 2019).

Big Data: "Big Data in health encompasses high volume, high diversity biological, clinical, environmental, and lifestyle information collected from single individuals to large cohorts, in relation to their health and wellness status, at one or several time points" (Pastorino et al., 2019, p. 23).

Big data adoption: "A process that allows an innovation to alter the infrastructure of an organization" (Baig et al., 2019, p. 2).

Big data analytics: The integration and processing of heterogeneous digital data with specialized tools to discover new relationships and discover actionable insights (Ristevski & Chen, 2018).

Big health data analytics: A predictive tool to help find a cure or diagnose people in a timely fashion (Milenković et al., 2019).

Boundary Spanning: "Interactions that are aimed at establishing relationships and interactions with external actors that enable the team to meet its overall goals" (Joshi et al., 2009, p. 732).

Bridging: “Involves attempts to acquire resources by creating interdependencies that avoid or lessen control that external resource providers possess or exercise” (Roundy & Bayer, 2019, p. 13).

Buffering: “Sealing off core operations from environmental influences and by engaging in internal actions to manage resources” (Roundy & Bayer, 2019, p. 12).

Capabilities: “A subset of resources, which represent an organizationally embedded non-transferable firm-specific resource whose purpose is to improve the productivity of the other resources possessed by the firm” (Akter et al., 2016, p. 115).

Cloud Computing: The practice of using a network of remote servers hosted on the Internet to store, manage, and process data, rather than a local server or a personal computer (Xu et al., 2018).

Data: “Is a set of symbols that represent the properties of events and objects” (Laitila, 2017, p. 6).

Data health ontologies: Using big data to identify links between data and patient diagnosis (Chen et al., 2012).

Data monetization: The process of creating new value and revenue from data (Ylijoki & Porras, 2018).

Digital data: Data recorded in an electronic format that can be analyzed via computer algorithms (Stryk, 2015).

Data science: “Collection of fundamental principles that promotes taking information and knowledge from data” (Vassakis et al., 2018, p. 8).

Effective use: Is the use of a system in a way that increases the achievement of goals (Surbakti et al., 2020)

Firm performance: “Resources create more economic value than marginal value and the competitors are unable to copy such capabilities and relevant benefits” (Akter et al., 2016, p. 115)

Federated digital data architecture: A digital data management approach that enables interoperability and data sharing among disparate groups (Kumar et al., 2018)

Information asymmetry: The condition in which one group or individual has superior and more actionable data than another (Bergh et al., 2019).

Intellectual capital: “Sum of knowledge, information, intellectual property, and experiences that can be used to create [value]” (Gravili et al., 2021, p. 263).

Machine learning: A method of AI in which a machine analyzes data consisting of natural language and applies it to structured data (Trifirò et al., 2018).

Neural networks: A method of AI in which a set of algorithms designed to recognize relationships in data through a process that mimics the way a human brain operates (Chen et al., 2012).

Organization: “(1) a multi-agent system with (2) identifiable boundaries and (3) system-level goals (purpose) toward which (4) the constituent agent’s efforts are expected to make a contribution” (Kretschmer & Khashabi, 2020, p. 87).

Organizational performance: “A set of measures and information that is used to increase the level of optimal utilization of facilities and resources to achieve goals in an economically efficient and effective way” (Tolici, 2021, p. 166).

Organizational separation: The structuring of distinct organizational units with common goals or functions (Dasí et al., 2017).

Power: The ability or authority to influence the actions of others (Menz, 2012).

Precision medicine (aka personalized medicine): Medical care designed to optimize efficiency or therapeutic benefit for specific groups or individual patients (Milenković et al., 2019).

Resources: "Tangible and intangible assets used by the firms to conceive of and implement its strategies" (Akter et al., 2016, p. 115).

Strategic interdependence: A relationship designed to minimize the risks of a partner's lack of knowledge-creating a condition to enhance a common technological understanding (Siachou et al., 2021).

Assumptions

This study has several assumptions that facilitate exploring the organizational design choices triggered by the high information asymmetries BDA implementation. Fundamental assumptions are the foundation on which the scientific approach is based (Haas, 2020). Further, according to Leedy and Ormrod (2015), assumptions are conditions taken for granted in the research design regarding the research problem and are presented for other researchers to evaluate against their assumptions. The following paragraphs address the central assumptions of this study.

Hospital administrations recognize the benefits of BDA and desire to increase reliance on BDA to improve data-driven decision-making capabilities. Second, hospital administration recognizes the power BDA experts hold given their superior, actionable information. Thirdly, and most important for this study, hospital administration desire to reduce information asymmetries caused by BDA within the organization.

There are also assumptions about the interview participants in this qualitative case study. First, it was assumed that participants would be familiar with the hospital BDA implementation strategy and the associated concepts and terminologies. I also assumed that participants possess the authority to make or influence organizational design choices. A third assumption was that participants might require orientation to the constructs and phenomena of this study as they have agency and may address themes not initially considered in the research design (Windsong, 2018). Fourth, it was assumed that participants would be truthful during the data collection process and not include their personal biases in their responses. The last assumption was that the interview participants can read and understand English.

Scope and Delimitations

The scope of this study is a single U.S. hospital that has implemented BDA into its operational paradigm. Furthermore, this study is delimited as it focuses on hospital administration's absorptive organizational design choices to reduce information asymmetry with BDA experts. Corporate design strategy within this study included M&A, joint or intra-organizational ventures, changes in the BOD, political or regulatory activities, and executive makeup or structure changes, all elements of RDT.

Non-U.S. hospitals were excluded from this study for accessibility and operational reasons. First, accessibility to non-U.S. hospitals and face-to-face interviews would be too costly. As such, my study borrows from the designs of Dremel et al. (2020)

in two ways; I conducted semistructured face-to-face interviews to build rapport and gather the overall context of the information asymmetry phenomena, followed by an augmented member checking process targeting the specific conditions and circumstances motivating the design actions taken. Second, operationally, U.S. hospitals substantially differ from non-U.S. hospitals. For instance, the United States spends far more on healthcare than any other developed country (Zeadally et al., 2019). Thus, although all hospitals could benefit from the cost-savings potential of BDA, the results of this study could be most significant for U.S. hospitals. Furthermore, the U.S. healthcare system is predominantly private compared to the public systems of other developed countries (Reibling et al., 2019). The preceding suggests that the results of an investigation of information asymmetry and the impact on organizational design choices would be well-suited for U.S. hospitals.

I evaluated several theoretical frameworks before determining that RDT is the most robust predictive lens through which to view the phenomena of this study. BDA has been extensively viewed through resource-based theory and its extension, dynamic capabilities view. Both resource based view and dynamic capabilities view theories are built upon RDT but are too narrow in focus for this study. For instance, rather than focusing on reducing uncertainty, as with RDT, they address using available resources to differentiate and gain a competitive advantage (Hillman et al., 2009). As mentioned, this study is not concerned with the BDA adoption process. Similarly, contingency theory is another dominant theory in the BDA domain. Contingency theory, as with RDT, focuses on reducing uncertainties, but contingency theory predicts environmental conditions faced by firms significantly influence organizational strategies and structure.

Alternatively, there is a domain of literature on the BDA adoption process dominated by diffusion of information theory. Diffusion of information focuses on why innovations spread throughout an organization (Fiorini et al., 2018). The research problem of this study is not concerned with BDA adoption. Instead, it focuses on the lack of research into the conditions and circumstances influencing organizational design choices to reduce information asymmetries. In short, RBV, dynamic capabilities view, and diffusion of information theories are centered on the decision to adopt process or the mechanisms in which innovation spread and, therefore, not appropriate for this study. Instead, the research problem requires the predictive theoretical framework of RDT in which to be viewed.

The condition of information asymmetry resulting from BDA adoption has been widely studied through agency theory, signaling theory, RBV, institutional theory, and social network theory (Bergh et al., 2019). Again, RDT is best suited for this study because the theory predicts that hospital administration will take a prescribed set of organizational design actions to reduce information asymmetry caused by BDA implementation.

The results of this study have limited transferability to other industries and populations for several reasons. As previously indicated, I employed a single critical case study design, which has limited transferability, according to Yin (2018). Second, U.S. hospitals have a unique operating model compared to other developed countries.

Theoretically, the results may test the boundaries of RDT within the healthcare paradigm and operationally may inform organizational design choices that improve BDA adoption.

Limitations

This study of organizational design choices has several limitations and barriers, which, according to Theofanidis and Fountouki (2018), are essential to acknowledge to improve the quality of findings and evidence interpretation. First, scholars have suggested that BDA implementations' analyses are context-dependent. These findings limit the study because hospital organizational practices are not standardized and likely geographically dependent (Zeng & Glaister, 2018). Additional limitations include access to interview participants of the case organization and access to organizational documentation. A significant barrier to this study was identifying a hospital that previously implemented an organizational change due to the use of BDA. Lastly, service fees charged by and enforced policies for external research of the case organization's institutional review board are a barrier to this study.

Significance of the Study

This study is significant because it helps fill a gap in understanding by focusing specifically on the influences of information asymmetry created by BDA on organizational absorptive design choices made by hospital administration.

Significance to Practice

The significance of management practice is threefold. First, understanding the organizational design configurations that reduce information asymmetry resulting from BDA could improve healthcare organizations' firm and organizational performance.

Second, management practitioners may benefit from having new tools and targeted corporate strategies to assist healthcare leaders in adjusting to a high information asymmetry from BDA. Third, the results of this study may benefit human resource departments and BODs with a better understanding of the antecedent qualities of chief executive officers (CEOs), chief information officers (CIOs), and chief digital officers (CDOs) for BDA-oriented organizations.

Significance to Theory

The theoretical foundation for this study is RDT, which suggests that hospital administration will take specific actions to reduce dependence on external resources. However, according to Hillman et al. (2009), future research must explore the dividing line and the appropriate environment for RDTs' relevance. More specifically, establishing patterns of responses to external resource constraints and to what extent specific industries benefit from reduced external resource constraints. To this end, the significance of this study to theory is that the results may test the boundaries of RDT within a hospital corporate design context.

Significance to Social Change

Reducing healthcare costs has never been more imperative, as the United States spends far more on healthcare per capita than other countries with similar life expectancies (Bidgoli, 2018). Estimates place waste from inefficient healthcare operations from $191 billion to $282 billion of healthcare costs (Shrank et al., 2019). These costs could be directed toward improving healthcare outcomes. The significance of this study to social change is twofold. First, the results of this study may increase the adoption of BDA, which could improve patient clinical outcomes, resulting in positive social change. Second, the results may contribute to lowering healthcare costs from increased efficiencies that may raise accessibility and availability resulting in positive social change (Milenković et al., 2019; Raghupathi & Raghupathi, 2014; Wetering, 2019).

Summary and Transition

This qualitative single critical case study aimed to improve the understanding of the conditions and circumstances surrounding the organizational design choices made by hospital administrations to reduce the information asymmetry created by implementing BDA. I viewed this study through the lens of RDT, which predicts that hospital administration will take specific organizational design actions to reduce the information asymmetries caused by implementing BDA.

This study is significant for several reasons. First, this study may test the boundary conditions of RDT in a healthcare context. Second, this study may create new tools, such as prescriptive implementation models for practitioners who implement BDA in a hospital setting. Lastly, the results of this study may be significant for positive social change as it may increase the adoption of BDA in hospital administration resulting in a positive social change.

Chapter 2 presents an analysis of the current literature through the lens of RDT regarding the phenomena of BDA, information asymmetry, and organizational design choices. Chapter 3 will provide an overview of the research method and design. Chapter

4 will present the results, and Chapter 5 will provide a discussion, conclusions, and recommendations.

Chapter 2: Literature Review

BDA healthcare literature is replete with strategic alliance scholarship (He et al., 2020) and collaborative organizational strategies (Akter et al., 2016). However, there is no research on the costly absorptive organizational design choices hospital administrators face in high information asymmetric environments (Al-Badi et al., 2018; Bergh et al., 2019; Mandlik & Kadirov, 2018). The purpose of this qualitative single case study was to explore the circumstances and conditions that influence hospital administration absorptive organizational design choices to reduce information asymmetry associated with BDA. I used RDT as a lens to view the research problem. RDT predicts that hospital administration will take a prescribed set of actions to limit dependence on external resources—specifically, measures such as M&A, BOD adjustments, intra-organizational changes, executive changes, or political acts that may include regulatory activities.

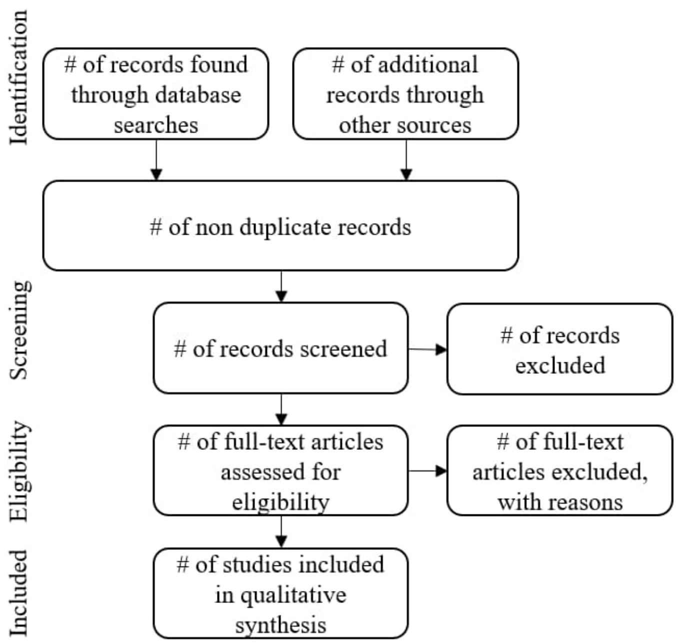
I conducted a systematic literature review that included a search strategy with explicit inclusion and exclusion criteria, resulting in 66 articles. In this chapter, I provide a detailed description of the systematic literature review process. Second, I present an argument for using RDT to explain the research problem and relevant RDT research. Next, I give a brief synthesis of the current literature regarding BDA and a rationale for selecting the concepts of my study. Then, I provide an exhaustive review of the BDA literature, concluding with a summary and transition to Chapter 3: Research Method.

Literature Search Strategy

The data collection method for this literature review was a systematic review of the research literature. Employing the systematic method, I methodically searched the literature based on inclusion and exclusion criteria, critiqued the literature, and assessed its quality of evidence. This method is appropriate because of the lack of BDA research regarding organizational design strategies. The systematic review is exhaustive and includes recommendations for practice, unknowns, and uncertainties of current findings. An essential strength of systematic review is that it is fully transparent in the reporting and is replicable (Grant & Booth, 2009). The flow diagram in Figure 4 represents the systematic review process.

Figure 4

Systematic Review Phased Approach



Note. Adapted from “The link between Industry 4.0 and lean manufacturing: Mapping current research and establishing a research agenda” by S. Buer, J. Strandhagen, and F. Chan, 2018, *International Journal of Production Research*, *56*, p. 2929. Copyright 2008 by Taylor & Francis Group.

Data Extraction and Analysis

Key constructs and research findings were compiled from citations published from 2017 through 2021. The following review includes peer-reviewed qualitative journal articles within the time frame except for one seminal work and a few quantitative articles where appropriate (Finfgeld-Connett & Johnson, 2013; Mingers et al., 2012). The data sources and the rationale for their use are listed in Table 1. The search terms and results are in Table 2. I imported each citation into EndNote bibliography management software, where I removed duplicates. Specific elements of each citation were manually extracted to aid in constructing the literature review. After extraction, aspects that were evaluated included the analytical method, research design, research question, topical relevance, sample population, and the study's main findings.

The quality of each peer-reviewed citation was categorized as either high or low. I categorized citations as high quality according to two criteria and included them in the literature review. The first was research design quality, a guideline posited by Anastas (2004), focusing on evaluating the clarity of the research question, data collection method, and analysis. The second criterion was the journal h-index score. Borrowing from Mingers et al. (2012), I included articles from journals with an h-index score greater than 51 in the literature review. I gathered the h-index score for each journal from the Scimago Journal & Country Rank website (https://www.scimagojr.com/). The h-index expresses the number of articles (h) that have received at least h citations. Thus, the index quantifies the journal's scientific impact and productivity (Mingers et al., 2012). Several indicators are used to evaluate journal and research performance, but the h-index is very effective and widely available (Mingers & Yang, 2017). Articles from journals with an h-index score of less than 51 (low quality) and articles with less than favorable research design quality were excluded. Also excluded were literature reviews, editorials, articles in medical journals (e.g., *Multiple Sclerosis Journal*), and journals that are not healthcare, business, or management focused.

Table 1

Scholarly Databases and Rationale for Searching

Database	Rationale
ABI/INFORM Collection	This collection includes 2,000 full text resources and covers a wide range of business, management practice and theory, health administration, corporate strategy, and competitive landscape.
Business Source Complete	This collection includes business, marketing, management, health administration, accounting, banking, and finance.
Computer Science Database	This collection includes journals covering the topics of health informatics, database design, and technology management.
Emerald Insight	This collection includes over 300 journals in the subject areas of management, health administration, finance, criminology, and social media.
ProQuest Health & Medical Collection	This collection includes topics such as health administration.
SAGE Journals	This collection includes topics such as psychology, political science, management, health administration, and education.
Science Direct	This collection focuses on the life and physical sciences, medicine but also includes topics such as social sciences and humanities.

Note. Information derived from *ULRICHSWEB Global Serials Directory*. Copyright 2021 by ProQuest.

Table 2

Database Search Strategy and Results

Search strategy	Items (before removing duplicates)
Big data analytics AND Qualitative AND Organization AND Healthcare OR Health care	697
Resource dependence theory AND Information Asymmetry AND Organizational AND Healthcare OR Health care	180
Total	877
Remaining articles after duplicates removed	430

The following sections present an analysis of relevant RDT literature and a rationale for using RDT as a framework for this study.

Theoretical Foundation

The theoretical framework that grounds this study is Pfeffer and Salancik's (1978) RDT, which has been widely studied in management and business scholarship (Bergh et al., 2019). The underlying theme of RDT is leadership control of external resources, and the central assumption of RDT is that leadership will tend to avoid dependence on external resources toward making others dependent on theirs. Applying this assumption to the research problem suggests that hospital administrators will undertake actions to reduce reliance on external BDA resources, such as collaborations, alliances, and organizational changes (Wry et al., 2013).

Although widely studied in management scholarship, RDT is not without criticism. Decades after its inception, its creators lament that the theory's practical use has been reduced to little more than a metaphor about organizations (Pfeffer & Salancik, 2003). Critics of the theory also point to its static and verbose conceptualizations that have been eventually refined over its lifetime (Akter et al., 2016). Wry et al. (2013) argued more precisely that RDT's appeal in scholarship is more a passing reference to say power and resources matter regarding a phenomenon. They further stated that those same scholars declined to engage with RDT's unique theoretical claims and nuanced arguments. Hillman et al. (2009) pointed to RDT's lack of clear boundary conditions and delineation between power asymmetry and mutual dependences may contribute to its limited use. In any case, proponents of RDT contend that the theory remains a critical perspective to understand organizational environmental relationships (Drees & Heugens, 2013).

The connection between RDT, the phenomena of BDA, and information asymmetry is the physical, organizational separation between hospital administration charged with controlling its digital data resources and the BDA experts that can derive actionable information from those resources. In addition, the lack of broad-based BDA capabilities coupled with the embryonic state of BDA technologies, particularly in healthcare, may contribute to its concentration of BDA resources with technology groups, as illustrated in Figure 3. The following section presents a cursory review of some relevant RDT literature related to the nature of this proposed study.

RDT Research

RDT literature regarding its predicted activities associated with healthcare is limited. RDT suggests that organizations will undertake actions to reduce uncertainty and reliance on external resources to shore up their business model. These actions include

M&A, joint or intra-organizational ventures, changes in the BOD, political activities (including regulatory actions), and executive change actions (Hillman et al., 2009). Most RDT research includes activities such as strategic alliances, networks, business groups, and supply chain management (Prasad et al., 2018). Overall, political activities and executive succession are not explored as often as M&A, inter-organizational structural activities, and BOD activities (Hillman et al., 2009). The following paragraphs provide an overview of how the predicted activities of RDT have been applied in the research domains of the supply chain, automotive manufacturing, government service, healthcare, and IT domains.

Political Activities

Through a lens of RDT, specifically its dimension of political activity, Prasad et al. (2018) investigated the linkages of big data in Indian non-governmental humanitarian supply chain networks. The authors attempted to uncover the connections between big data and supply chain outcomes and how big data were associated with humanitarian supply value streams. The authors used a case study approach to gather secondary data from donors and suppliers. They then applied thematic analysis to develop a resource dependence model to improve the operational effectiveness of supply chains. The authors viewed the problem from an asymmetric power (which is synonymous with information asymmetry) (Salancik et al., 1978), and resource perspective then applied the attributes of big data. The authors found that donors (e.g., corporations, government authorities, and local councils) may indirectly exert power over nodal supply chain actors by demanding big data analytical products. Additionally, Prasad et al. determined the degree of dependence that the supply chain actor regulated the power asymmetry. The results of this study shows how specific dimensions are applied to a phenomenon as opposed to the entire RDT framework. A similar approach was applied in the following studies.

Peretz (2019) investigated the cause of organizational decline through the lens of RDT, specifically the overdependence on government relationships of an Israeli firefighting service. The decline in the study is defined as successive resource reductions that invoke a response by management. Peretz employed an intrinsic case study approach to explain how the lack of resource control can lead to organizational decline. The author determined that a lack of clear budget policy and reduction in resource allocation were the two factors leading to a service decline. Similarly, Sutton et al. (2021) found a link between uncertainty and an increase in managements' relationship to political activities. The results of these studies show how governing jurisdictional authorities exert control over dependent actors.

Low-power actors can also influence information asymmetries. The authors' Shu and Lewin (2017), employing a qualitative multi-case study approach, apply the political dimension of RDT to how low-power actors can shape the negotiating environment in the Japanese auto manufacturing context. Based on RDT extant literature, low-power actors typically form coalitions with business or regulatory associations to reduce power asymmetries (Shu & Lewin, 2017). Other scholars point to how low-power actors use creative strategies or inter-organizational politics to advance their agendas (Bouquet & Birkinshaw, 2008). However, in the former case, low-power actors allied with environmental activist groups to mitigate the power asymmetry with competing business organizations (Shu & Lewin, 2017). The results of their study extend the concept of power beyond traditional dyadic relationships.

BOD Changes

RDT can be used to explain the behavior of a BOD within an entrepreneurial start-up network. The authors Galvão et al. (2019) applied RDT, specifically the activity of interlocking directorates, to the role of incubators. The authors qualitatively investigated the network creation process and the link between collaboration with resource-starved start-ups and incubators'. The authors gathered data via a multi-case approach from expert interviews. The authors found that incubators (intermediaries) play a resource bridging role in developing collaborative networks.

Furthermore, the informal networks bridge resources that start-ups cannot provide themselves (Galvão et al., 2019). These results underscore the notion that resource-starved organizations endeavoring to implement BDA may use intermediaries to bridge resource gaps. Additionally, a bridging strategy may be a low-cost organizational design approach. Geographical and institutional separation have also been shown to influence the decision to interlock directorates due to barriers in information processes (Sanchez et al., 2019).

Board member behaviors can influence firm performance. In a multi-case study through a multi-theoretical lens that included RDT, Chambers et al. (2020) investigated the behaviors of healthcare boards that improve firm performance in the United Kingdom. The authors focused on the concept of board interlinkages with external dependencies toward enhancing the reputation and relationships of the healthcare institution. The authors found that boards via a boundary-spanning process improved reputation and relationships (Chambers et al., 2020). Thus, the boundary-spanning process resulting from the use of RDT as a lens to explain board interlinkages represents an extension of the theory. Furthermore, the boundary-spanning strategy may be another cost-effective approach for resource-starved organizations.

Joint Ventures and Collaboration Activities

Resource management among competitors may require novel forms of cooperation. Broek et al. (2018) conducted a case study investigating cooperation among four Dutch hospitals to optimize a talent management pool. The authors utilized RDT to explain why various competing hospitals would collaborate over their human capital requirements. They framed the phenomena as *coopetition*, which is cooperating within a competitive resource environment. The authors identified three themes: coopetition's role, the rationale for coopetition, and cooperation versus competition. The authors suggested that the perceptions of organizational actors on *coopetition* may differ and hinder cooperative innovation with competitors. At the same time, perceived shared problems and resource constraints may stimulate coopetition (Broek et al., 2018). These findings also suggest resource-starved organizations may elect to implement coopetition over control of vital external BDA resources.

Alliances are a means of value creation from pooled resources (Das & Teng, 2000). Sarcone and Kimmel (2021) employed a case study approach through the lens of RDT to investigate the factors influencing successful rural hospital alliances. Sarcone and Kimmel collected data via open-ended structured interviews with key stakeholders along with publicly available secondary data. These findings highlight how successful alliances rely on key organizational capabilities throughout the entire alliance formation process and awareness of critical milestones and proactive corrective actions. The results of their study suggest these key organizational capabilities may evolve over the alliance process.

M&A Activities

The prior studies used the RDT dimensions of political, joint ventures, and collaboration to view the research problems. The following study investigates the M&A dimension in a healthcare context. Some M&A context before introducing the study. RDT is an external perspective on why firms merge or acquire other firms. Pfeffer and Salancik (1978) suggested three reasons why firms engage in M&A: (a) to reduce competition, which in a healthcare context is typically when hospital administration decides to acquire other hospitals to grow market share or improve the quality of patient care (Monteros et al., 2021); (b) to diversify operations, and (c) to manage business-critical interdependencies (Pfeffer & Salancik, 1978). The latter is applicable as it relates to my proposed study.

Pierce (2019), in a quantitative study of U.S. hospital mergers, investigated the organizational characteristics and environmental factors related to the merger. The problem was viewed through the lens of RDT. The authors gathered secondary data from various survey data sources and performed a bi-variate statistical analysis. The authors found that motivating factors for hospital mergers were aligned with market factors and organizational characteristics such as ownership status and found limited support for performance metrics as motivating factors.

Bridging and Buffering Extensions of RDT

Emerging ecosystems with limited resources may employ bridging and buffering strategies to garner necessary resources. In a recent study, Roundy and Bayer (2019) used RDT as a lens to investigate nascent entrepreneurial ecosystems in emerging economies. Their study examined how entrepreneurial managers handle the barrier to grow existing, create new, or acquire necessary resources. Roundy and Bayer (2019) critically reviewed the literature to propose an extension to RDT within an entrepreneurial ecosystem that addresses managerial intermediate and more extended term actions. The authors identified a positive relationship between RDT and strategies of bridging and buffering. *Bridging* is a strategy in which leadership accepts external control of limited resources but incorporates alliances and vertical integration to limit external control (Roundy & Bayer, 2019). Bridging has also been shown to be an effective strategy in public sector contracts, but the practice requires active resource management and special data processing skills (Lengnick-Hall et al., 2020). On the other hand, *buffering* is a strategy to cordon off essential resources protecting them from external control (Roundy & Bayer, 2019). The proposed bridging and buffering extension is applicable in my study's context as they represent cost-effective alternative organizational strategies.

The Rationale for RDT

The studies outlined above employed RDT to describe a phenomenon via individual dimensions or combined it with other organizational theories. In those cases, the scholars investigated a particular activity related to the phenomenon of interest. As mentioned, there is currently no research on the conditions and circumstances affecting costly organizational absorptive choices resulting from BDA implementations in the healthcare setting. Therefore, I used all the dimensions of RDT as a lens for my study. Results of my study may serve as a basis to identify a specific dimension worthy of further research.

Absorptive choices, in a healthcare context, could be any sub-set of the four prescribed RDT activities. Results of my study may provide insight for a deeper investigation into specific dimensions of RDT regarding absorptive organizational choices in healthcare. The following literature review presents examples of board interlinkages, intra-organizational ventures, joint ventures, partnerships, external collaborations, M&A, and intra-organizational collaborations caused by or predicated to BDA implementations. One study revealed evidence that a 3rd party non-governmental actor could be a factor in securing necessary BDA resources raising the prospect that the boundary conditions of RDT may need to be reassessed. Furthermore, according to the literature, there is evidence that some organizational design strategies can be durable and transformational, while other scholarship points to transitory strategies. The literature suggests any of the above configurations may apply in a healthcare context.

As outlined in earlier sections, the specific connection of this study to RDT is that BDA competence is the vital resource hospital administration will seek to control to reduce information asymmetries. Costly absorptive organizational design strategies to exert control over resources may be the appropriate approach in healthcare. This resource control may be accomplished by reducing the physical, organizational separation (e.g., structural or hierarchical changes), changes in board makeup or competencies, intra-organizational collaborations, joint ventures with BDA resources, or M&A BDA resources. Alternatively, as outlined in the above studies, resource control may include novel organizational design strategies such as bridging, buffering, or boundary-spanning.

BDA Literature

Three threads weave through the BDA management literature outlined below. First, data quality appears to be the keystone capability to use BDA effectively. Second, new resources, capabilities, and intellectual capital must be acquired or created. Third, and most relevant for the nature of my study, new or novel organizational configurations are required. Organizational strategies, according to the literature, may either be transitory or organizationally transformative and durable. Finally, it is also evident in the literature that the threads of research are interlocked and interdependent. These connections mean hospital administration should consider many factors (e.g., data quality, resources, competencies) when making organizational design decisions, particularly costly absorptive ones.

Limitations of Current Steam of BDA Literature

I observed an overreliance on prescriptive models, selection bias, and a lack of validated survey instrumentation in the literature presented below. Prescriptive models and frameworks are manifold throughout the review. As such, study results are more applicable to practitioners than management theoreticians. Second, selection bias may be a factor in BDA qualitative scholarship, particularly in healthcare; sample populations are predominantly CIOs, CDOs, and IT professionals rather than end-users of BDA technology. To improve robustness, scholars should use a broader population of experiences.

Finally, the literature review reveals a lack of validated survey instrumentation for quantitative BDA scholarship. This deficit may be due to the embryonic nature of the BDA phenomenon. In any case, according to Straub (1989), the lack of validated quantifiable measures raises questions about the generalizability of study results. Nevertheless, most studies use techniques to mitigate common method bias, non-response bias, Harman's one-factor test, and pilot studies. Alternatively, an adaptive survey design may be an appropriate intermediary technique on the path to quantifiable confirmatory BDA research. Especially given the need for broader group representation. Adaptive survey design use techniques and parameters to minimize imprecision and bias across disparate informant groups (Burger et al., 2017). More BDA-relevant survey instrumentation can improve the generalizability of results but can only be achieved after deeper investigations into the fundamental BDA phenomena.

The following sections are organized as follows. First, I present a rationale for selecting concepts, followed by a high-level review of BDA in healthcare. The literature review is then divided into four sections of organizational, resource, and role configurations concluding with a review of studies on information asymmetries.

The Rationale for Selection of Concepts

This research represents an entanglement of absorptive organizational strategies and information asymmetry concepts. The former idea was selected for its relationship to hospital financial performance and the latter because the implementation of BDA, according to the literature, generates high information asymmetries among organizational groups.

Financial performance is a concern in healthcare as the United States spends more than any country with similar results, and there is no indication that this trend is abating. Since the Primary mission of hospital administration is creating an equitable, accessible, and efficient healthcare system (Pozgard, 2014), there is an inherent obligation to investigate innovative means of reducing transaction costs, such as BDA technologies. Yet absorptive organizational activities are costly and run antithetical to traditional cost-saving strategies. As such, hospital administration should make absorptive organizational decisions after careful deliberation.

The phenomenon of information asymmetry is not unique to healthcare BDA. The literature is replete with studies addressing the organizational gaps in BDA resources and capabilities from various industries, countries, and contexts. However, the phenomenon is amplified in healthcare as digital patient data is a highly regulated resource and must be strictly controlled.

BDA and Healthcare a New Paradigm

The new healthcare paradigm is value-based and digitized. BDA is highly relevant in this new business model as it provides new metrics and tools that enable new capabilities to sort patient populations and analyze operational processes (Hogle, 2019). Organizations must build the technological infrastructure to house and process the massive volume of healthcare data and invest in the human and intellectual capital to shepherd populations into this new paradigm (Pastorino et al., 2019). Paramount to this effort is the gap in technical capabilities and healthcare implementation capabilities (Jastania et al., 2019). Two facts illustrate the incipiency of BDA. First, the role of CDO, charged with managing new digital business models, did not emerge until 2003 (Kunisch et al., 2020), and the term big data was only first introduced in 2005 (Krithika & Rohini, 2020). Unfortunately, adopting BDA is not the panacea claimed by digital experts; BDA has its challenges, particularly among the clinical community (Chin-Yee & Upshur, 2019). Evidence suggests data quality is the biggest challenge for organizations to differentiate using BDA (Côrte-Real et al., 2020). Other proponents suggest that digital data needs to be managed with scientific methods to improve BDA quality (Jastania et al., 2019). Second, the new healthcare paradigm will require novel resources, capabilities, and organizational structures.

The following literature review is divided into the domains of BDA in healthcare, organization configurations, resource configurations, and role configurations. Information asymmetries between stakeholder actors follow these sections. Last, a summary of the findings will be presented along with a transition to the results, Chapter 3.

Organizational Configurations

Understanding how organizations compete for finite digital resources is essential for BDA. Velthoven et al. (2019) investigated how healthcare organizations can compete for digital resources. The authors viewed the problem through an integrated framework of digital opportunities, which helps organizations change by characterizing the digital landscape in which they operate. The framework prescribes four pathways. First, change can occur via make unilateral changes faster than competitors. Second, collaborate with technology organizations. Third, collaborate with competitors and create a new business model. The authors conducted a workshop with 12 stakeholders throughout the Swedish healthcare industry. Their study showed that all four digitization pathways were utilized (Velthoven et al., 2019). A similar qualitative study of service systems showed that collaboration with various internal stakeholders and skill sets a critical factor in managing resources (Akter et al., 2019). The results of these studies suggest that hospital administration must investigate the resource availability from non-traditional sources.

Digital technologies such as BDA enable new operational paradigms. For example, Biloslavo et al. (2020) found that digital technologies enable new sustainable business models, although they need legitimacy from internal and external stakeholders. Moreover, in the Swedish study, competitive pressure was also found to be a strong determinant of BDA adoption outside the healthcare domain (Lai et al., 2018; Verma & Chaurasia, 2019; Yadegaridehkordi et al., 2020). The results of these studies suggest two main points. First, there is a high degree of information asymmetry in healthcare related to digitation initiatives. Second, both collaborative and absorptive organizational strategies are relevant for BDA implementations. Furthermore, the study highlights the nature of the healthcare competitive environment may be a factor in design decisions.

Innovative Capacity Capability is Context Dependent

The moderating role of IT practices increased organizational innovative capacity, although its relational and trust capital is not well understood. In a quantitative study, Cabrilo et al. (2020) used secondary data from 102 publicly traded Taiwanese firms to find that trust embedded in intercompany relationships correlated to increased innovative capacity. The results also confirm the critical role of IT advancement in amplifying the effect of relationships (i.e., internal and external) and trust formation on innovation performance (Cabrilo et al., 2020). In addition, BDA has also been shown to improve organizational agility through innovative capability (Ashrafi et al., 2019).

These findings are essential for hospital administration for a couple of reasons. First, these results suggest a BDA absorptive organizational strategy may improve the innovative performance. Second, the findings of this study suggest that organizational configurations are context-specific. More specifically, the structural position of BDA experts. The study findings may have limited generalizability into the U.S. hospital paradigm as both value streams are highly complex, and the automotive industry is not confronted with patient data protection and privacy barriers. Finally, these studies show how IT may positively impact an organization's innovative capacity, an essential resource for BDA.

Independent Digital Transformations are Unlikely

Organizations rarely possess the technical or intellectual capability in new technologies to undertake a digital transformation such as BDA without external support. On this point, little is known as to whether organizations can perform digital transformations without external support. The authors Siachou et al. (2021) found alliance knowledge a prerequisite to digital transformations. Further, the capability of absorptive capacity (high and low) and strategic interdependence (symmetry vs. asymmetry) are boundary conditions to this relationship. Along this same line of reasoning, there is also a strong relationship between the effective use of BDA and performance mediated by absorptive capacity (Torres et al., 2018). These findings further support the assertion that digital transformations such as BDA are context-dependence. More specifically, external alliances are crucial for acquiring the necessary capabilities to enable a BDA transformation.

BOD and Strategic Interdependence

The interaction between the BOD and top management is critical, especially in volatile working environments such as healthcare. BDA implementations require a close orchestration of resources throughout the hospital value chain adding to the complexity. According to Luciano et al. (2020), the working relationship between the top management team and the BOD should be interdependent and independent. In addition, the authors suggest the working environment should allow for a free exchange of ideas, particularly in complex and dynamic market environments (Luciano et al., 2020). These results lend credence to the notion that hospital administration and the BOD should direct resources toward developing strategic interdependence, and mitigating information asymmetries, particularly BDA.

IT Centrality Impacts Firm Performance

The relationship between the relative organizational position of IT to organizational performance is not well understood. Paré et al. (2020) employed a quantitative study approach with survey data from 72 Canadian hospital CIOs to investigate the relationship between performance and IT structural position. Interestingly, the authors did not provide a concise definition of organizational performance but did refer to the alignment or participation of the IT organization in the strategic initiatives of the hospitals in this context. In addition, the authors addressed potential common method bias by embedding independent and dependent variables in separate survey parts for credibility. The study shows how IT can positively impact hospital performance from a CIO's perspective (Paré et al., 2020). A separate Canadian healthcare study found organizational design strategies linked to hospital organizational performance (Chubbs, 2020). Worth noting, limiting sample participants to CIOs suggest sample bias may be an influence on the findings. Alternatively, including CEOs in the survey sample would have provided a unique perspective into the perceived benefits of centralized IT organizational resources, as they have jurisdictional authority over all hospital strategic initiatives. Nevertheless, the study results suggest that IT position within the organizational hierarchy coupled with alignment with strategic goals may positively impact hospital performance.

Oscillating Digital Capabilities Improves Implementation

Centralized BDA experts can be distributed as capabilities mature. Centralizing digital experts have been shown to save time and improve implementation efforts (Sulankivi, 2004). Moreover, scholars recognize that the roles of CDO and CIO complement one another are not well understood (Horlacher & Hess, 2016). A qualitative single case study aimed to distinguish the CDO role and comparable executive roles to implement a digital transformation (Schilling et al., 2020). The authors concluded that a CDO must facilitate the organizational learning process and adjust the learning process over time (Schilling et al., 2020). Thus, the results of this case are prescriptive and valuable for organizations endeavoring to undertake a digital transformation. However, these results are related to my study in that the authors suggest oscillating strategy by initially centralizing BDA experts followed by distributed experts as the organizational learning capability matures.

The oscillating capabilities strategy was also evidenced in a centralized digital leadership configuration linking intra-organizational stakeholders during digital transformations. Singh et al. (2019) viewed this phenomenon through a centralized governance structure lens. The authors employed a qualitative multi-case study approach, gathering data primary data from expert interviews. To ensure multiple perspectives of the phenomenon, the authors used snowball sampling. The authors found that CDOs need to be embedded in the organization and have both formal and informal duties (Singh et al., 2019).

Although none of the case organizations were in healthcare, the results of these studies suggest two main factors for hospital administration to consider. First, a digital transformation of an organization to utilize BDA is a process that begins with hospital leadership designing a digital transformation strategy followed by the acquisition of digital experts to implement the plan. Second, organizational design parameters are less critical than acquiring digital experts with the antecedent talent and expertise to implement the digital transition strategy. Lastly, and relevant for my study, the process implies hospital administration has the prerequisite digital knowledge to formulate a digital transformation strategy. Continuing to follow this logic further suggests that hospital administration may acquire digital expertise on an interim basis via non-absorptive activities such as partnerships or alliances.

Cross-Functional Boundaries

The studies above show that DT affects the organizational structure, but little is known about how these transformations affect output creation. Kretschmer and Khashabi (2020) considered the research problem through the conceptual framework of an organization. Kretschmer and Khashabi found that new interdependencies must be designed in a digital organization. Similarly, Corsaro (2019) determined that multiple BDA value streams exist in a healthcare setting, and leadership should consider how they are connected to cross-functional boundaries. Cross-functional boundary spanning was also relevant in an E-Commerce setting (Du et al., 2020). These findings suggest a strong link between BDA and organizational boundary spanning design choices. Further, these findings also indicate that BDA encourages reconfiguring tasks with an eye toward strategic interdependence of unit operations.

Along the same line of reasoning, strategic interdependence logic and the relationship between BDA capabilities and co-innovation are not well understood. Lozada et al. (2019), in a quantitative study of 112 Columbian firms, found evidence supporting a positive relationship between BDA capabilities and higher levels of co-innovation. Furthermore, Lozada et al. also highlighted the need for internal and external collaborative networks to the organization. From a different perspective, collaborative networks have also been shown to strengthen business models and stabilize operations in turbulent environments (Camarinha-Matos et al., 2019). These results suggest that novel organizational structures are relevant in BDA implementations.

Multi-Disciplinary Alliances as a Sociotechnical System

Group and corporate level alliances differ from multi-disciplinary group functions. The interplay between actors of multi-disciplinary groups is not well understood. Specifically, how organizational actors interact and how they mutually influence one another. The authors Marsilio et al. (2017) investigate this problem through the lens of a sociotechnical system (STS). This lens portrays an organization as an amalgamation of social subsystems of both people and the technical production process elements. The underlying assumption of STS is that the two subsystems must align to meet the organization’s goals (Marsilio et al., 2017). Marsilio et al. employed a qualitative case study approach, gathering primary data via interviews of medical device representatives and physicians from four Italian hospitals. The authors suggest that the interplay between interdisciplinary groups is a not sequential process and needs to be managed efficaciously as an integrated organizational whole to deliver the goals set by my leadership (Marsilio et al., 2017). These findings suggest hospital administration must factor in the behavior of multi-disciplinary medical teams when considering organizational design decisions. Furthermore, these teams should include or work closely with BDA experts (Akter et al., 2019; Migliore & Chinta, 2017).

Alliance Momentum

The sequential nature of the alliance or momentum is also relevant for corporate alliances as well. Park et al. (2018) investigate the formations of corporate alliances over time specifically, whether the formation occurs in a step-wise sequential manner or simultaneously. Organizational boundaries are established based on functional domains, emphasizing explorative and exploitative value chain charters (Park et al., 2018). Therefore, the formation of alliances is particularly relevant for hospitals lacking BDA resources. The authors conducted quantitative analysis on the airline industry, collecting secondary data from 32 carriers between 1982 and 1994. Using regression analysis, the authors calculated the airline's probability of forming an alliance given a specific month referred to as momentum. The authors note that these findings imply that alliance momentum with one particular functional focus evolves sequentially rather than simultaneously (Park et al., 2018). Also, there is evidence that competitive advantage alliance strategies change over time (Prescott & Shi, 2008). These findings are relevant for hospital administration considering alliances to resolve resource issues. Specifically, they should account for alliance formation's temporality and sequential nature.

Organizational Boundary Uncoupling

The process of organizational boundary uncoupling between stakeholders within a healthcare service provider context is not well understood. Therefore, Wiedner (2017) conducted a qualitative study to investigate the problem through the conceptual framework of organizational boundaries. This study included primary data from semistructured interviews with management and secondary data from community meeting observations and company documents. The authors found that boundary spanning may be a helpful strategy in the context of organizational integration and in enabling organizational separation by inhibiting boundary-breaching attempts and facilitating boundary closure (Wiedner, 2017). Furthermore, boundary spanning activities have also been shown to improve business efficiencies and lower transaction costs (Sun & Liu, 2021).

Nevertheless, the results of these studies suggest two strategies hospital administration should consider for organizational uncoupling. First, embed advocates in BDA functional groups to facilitate the boundary-spanning phenomenon. Secondly, hospital administration should consider designing organizational interdependencies between distinct stakeholder functional groups. These interdependencies will inhibit the reformation of legacy ties.

Top Management Jurisdictions

The CDO is an emerging role in which the operational jurisdiction is not well understood, particularly in the presence of incumbent authorities such as the CIO and entrenched IT groups. To investigate the jurisdictional boundaries, the authors Tumbas et al. (2018) conducted an exploratory study using open-ended interviews of 35 CDOs across various industries. Tumbas et al. viewed the research problem through an institution logics conceptual framework using the dimensions of goals, values, and prescriptions for a specific operating environment. Three logics processes were observed to contrast the CDO activities with related organizational functions, grafting, bridging, and decoupling (Tumbas et al., 2018). Singh et al. (2019) also found via multi-case study that a CDOs organizational vertically anchored position is necessary, and horizontal coordination skills are needed when undertaking complex activities such as a digital transformation. The results of these studies suggest unique jurisdictions should be established before absorbing new digital roles. The implications for hospital administration are two-fold. First, a digital strategy must be formulated, and second, the digital role needs clear jurisdictional boundaries to implement the hospital's digital strategy.

Hierarchical and Structural Power

As alluded to in the prior studies, jurisdictional boundaries and hierarchical position are essential, but behavioral tactics are also relevant in securing resources. Brass and Burkhardt's (1993) seminal work on structural power and behavior found links between organizational hierarchy, network centrality, and behavior. The authors conducted a survey of seventy-five employees from a research and development group of a federal agency. The authors find that leadership can take strategic action to overcome a lack of resources. For instance, powerful actors with ample resources are less dependent on capabilities. Behavioral tactics mediate the power of centrally located actors. "The use of behavioral tactics, in turn, leads to increased resources and an advantageous structural position. Thus, the structure also mediates the behavior-power relationship (Brass & Burkhardt, 1993, p. 466)". A recent study confirms that expert and structural power are antecedents to information control within organizational boundaries (Prior et al., 2021). These findings suggest that hierarchical position, behavioral tendencies, and the leadership style of digital healthcare experts influence resource control capabilities.

Technical Capabilities

Technical capabilities may also be a factor in healthcare organizational performance. Precisely, quality of care may be measured in patient readmission ratio and patient satisfaction. The authors of a 2019 study employed a fuzzy-set qualitative comparative analysis technique (Wang et al., 2019). The fuzzy-set qualitative comparative analysis approach is an asymmetric data analysis technique incorporating qualitative and quantitative methods (Pappas & Woodside, 2021). The authors, using this approach, find how BDA technological capabilities alone are insufficient to improve care quality. Instead, there needs to be a symbiotic relationship between BDA technical capabilities, analytical personnel skills, and organizational resources play a supporting role (Wang et al., 2019). The findings of their study support the notion that absorptive organizational strategies may be needed to acquire BDA experts within the organization. Furthermore, these findings highlight how organizational performance can be affected by dedicating resources toward developing intellectual capital.

Resource Configurations

The following sections present relevant BDA literature regarding various resource and capability configurations. Akter et al. (2016) defined *resources* as "tangible and intangible assets used by the firms to conceive of and implement its strategies" (Akter et al., 2016, p. 115). Additionally, embedded non-transferrable resources are used to improve firm productivity or performance (Akter et al., 2016). Lastly, according to RDT, leadership will seek to control external resources to shore up their business model (Wry et al., 2013).

BDA Capabilities are Context Sensitive

BDA implementation strategies are context-dependent. The connection between digital strategy formulation and implementation is often cited as to why organizations fail to extract value from initiatives such as BDA. The authors investigated a lack of alignment between BDA strategy formulation and implementation (Correani et al., 2020). The authors of this study employed a multi-case study approach using technology, agriculture, and a communication multinational case organization. Through the lens of digital transformation, the authors determined that successful implementation of BDA and AI technologies requires new professional roles, and incumbent employees may need to possess new skills or capabilities (Correani et al., 2020).

Moreover, organizational leadership must undertake measures to prevent competence obsolescence from meeting the demands of new digital work environments (Ghislieri et al., 2018). Each company used a different strategy. One company partnered with a third-party BDA firm; another created new roles to manage BDA capabilities specifically. The last company trained existing employees to work in a digital environment. Authors were not able to access failed digital transformation for confidentiality reasons. The authors used an inductive approach, member checks, and triangulation to arrive at the results (Correani et al., 2020). These studies suggest that firms may use radically different strategies to increase their BDA capabilities.

Capability Homogeneity and BDA Effective Use

The process of generating value from BDA requires capabilities across the entire organization. Brinch et al. (2021) investigate the organization-wide capabilities to generate value from big data. The authors employed a single case study methodology with embedded units of a Danish wind turbine facility. The authors gathered primary data through semistructured interviews and conducted an iterative data analysis approach through the lens of business process management and IT business value. A strategic alignment framework comprising human, IT, organization, performance, process, and strategic practices is used to identify 15 types of alignment capabilities and their inter-dependent variables fostering the value creation of big data. The authors found that process integration is essential for deriving business value from BDA (Brinch et al., 2021). Lai et al. (2018) arrived at similar results showing top management support for capability development and acceptance of outside support positively affected BDA effective use. Lai et al.determined these factors from quantitatively analyzing survey data from 210 Chinese organizations.

Similarly, organizations with high intellectual capital levels can better derive value and effectively use BDA (Elia et al., 2020). There is also a synergistic relationship between knowledge management and BDA (Wang & Wang, 2020). These findings suggest two strategies for BDA-oriented hospital administration to mitigate information asymmetries. First, the results show how important it is for firms to have mature BDA processes to derive value. Secondly, the findings suggest that embedding data processing capabilities throughout the organizations are essential, especially for strategically interdependent functional departments.

Incumbent Intellectual Capital and BDA Effective Use

BDA implementations are challenging, particularly in capability-starved environments. Leveraging existing resources and capabilities is a cost-effective approach to bridging resource deficiencies. According to De Luca et al. (2020), managers should identify incumbent actors within their organization best suited to actualize value from the use of BDA and empower them to take action. The authors' De Luca et al., surveyed 135 managers attending BDA and digital marketing courses. They determined a relationship between actors and available resources is based on the environment, so the goals and abilities are fluid over time. Through the lens of affordance theory, the authors model phenomena based on the goal-directed actors related to available resources. De Luca et al. found that BDA success depends on customer behavior pattern spotting, real-time market responsiveness, and data-driven market ambidexterity. BDA dynamic capabilities or ambidexterity in using external knowledge also explain BDA value's derivation in resource-starved environments (Shamim et al., 2020). The results of these studies suggest hospital administration encourages incumbent BDA proponents, especially when resources are limited.

The value of incumbent intellectual capital is further supported; according to Y. Wang, Kung, and Byrd (2018), an essential strategy for success in BDA implementation involves training incumbents to have the necessary analytical skills or adjusting job selection criteria. In addition, some scholars suggest BDA requires teams with heterogeneous skills (Santoro et al., 2019). Similarly, Doonan (2018), after surveying over 100 top digital executives, found a need to absorb BDA experts instead of partnering with BDA experts either within or external to healthcare.

Intra-Hospital Intellectual Capital and BDA Effective Use

BDA is used throughout the hospital supply chain; however, the benefits of BDA to the integration process and its impact on environmental performance are unknown. Benzidia et al. (2021) investigated the integration process through a digital learning framework. They conducted a quantitative study and surveyed 168 supply chain French hospital professionals. The authors performed a partial least squares analysis after several tests to mitigate common method bias were conducted. The findings showed that BDA and AI technologies significantly affect environmental process integration and supply chain collaboration. More specifically, the study found that hospitals with BDA technological means and the necessary intellectual capacity can mitigate uncertainties driven by operational variability and related to functional group interdependence (Benzidia et al., 2021). The results of their study suggest intra-hospital BDA intellectual capital has a positive effect on BDA effective use. According to Gravili et al. (Gravili et al., 2021), along with this line of reasoning revealed that investments in incumbent intellectual capital are more prosperous than investments in physical assets in a healthcare context. Both studies highlight the importance of organization intellectual capital in BDA environments.

Organizational Learning Capability and BDA Effective Use

Organizational learning is a cultural predecessor to intellectual capital. The relationship between organizational learning, BDA decision support, and hospital organizational performance is understudied. Investigating the relationship between learning cultures, the authors Arefin et al. (2021)used a quantitative approach to gathering survey data from 217 healthcare managers in Bangladesh hospitals. The authors found that hospital administration should focus resources on creating a learning culture to implement BDA solutions effectively. These results are consistent with a Taiwanese study that shows how BDA improves a healthcare organization's absorptive capacity (Wang & Byrd, 2017). Worth noting, the Bangladeshi healthcare business model is highly unregulated and substantially subsidized by the government, which starkly contrasts with the U.S. healthcare system (Joarder et al., 2019). Although the healthcare business models differ between the United States and Bangladesh, the results suggest that directing resources to develop organizational learning may positively affect BDA's effective use. In addition, unsupportive organizational cultures have been shown to impede BDA implementations. Factors such as a shortage of data experts, poor data quality, cyber-attack risk, and unsupportive organizational cultures impede implementation and utilization (Sumbal et al., 2019).

Technological Capabilities Drive BDA Adoption

Technological capabilities drive each stage of the BDA adoption process. However, there is a lack of understanding of the drivers to the BDA adoption process. According to Nam, J. Lee, and H. Lee (Nam et al., 2019), competition intensity was the only factor associated with the initiation stage, although organizational characteristics such as data quality and technical capabilities were associated with the adoption and assimilation stage. To arrive at the findings, Nam et al. (2019) first conducted a literature review through the lens of technology, organization, environment (TOE) framework, and diffusion of information theory to develop a model. Nam et al. then tested the model via a quantitative approach by gathering survey data from 170 respondents from Korean firms. Similarly, according to Akter et al. (2019), adopting BDA suggests organizations have the necessary resources, capabilities, and intellectual capital to adopt. The results of these studies reinforce the notion that acquiring or developing new technical capabilities and resources is critical for instituting BDA.

Transitory Resource Allocations

Effective resource management, essential roles, and archetype business process for BDA implementations are not well understood. To investigate this problem, Braganza et al. (2017) used a qualitative exemplar case study approach gathering primary data from semistructured interviews of BDA experts from a case organization that implemented multiple BDA projects. According to Braganza et al. (2017), the initial phase is where project leaders draw on experts from internal and external stakeholders. Also, during this phase, success criteria are established, and data sources are identified. The remaining two phases are the implementation and deriving value phases (Braganza et al., 2017). The results of their study suggest that BDA implementations could be transitory (e.g., finite begin and end dates) with clear success criteria. Mach-Król (2019) presents similar findings but adds that BDA implementations should also consider the organization's digital maturity level in the initial phase. Moreover, according to Mach-Król (2019), the project team could be disbanded post-BDA implementation. The findings from these studies suggest that less costly, and short-lived BDA organizational design strategies may be appropriate.

CEO Internal Coordination and IT Investments

The Healthcare CEO decision process regarding IT purchasing decisions is not well understood. However, a qualitative study of 14 German hospital CEOs found that the joint decision process encouraged a collaborative approach. Specifically, the CEO requested that the CIO better understand the financial issues of the hospital while the CEO inquired into the specifics of the IT and value propositions of the technology (Thye et al., 2017). In addition to collaborating with CIO, the CEO should also consider artifacts such as organizational maturity and quality of prior decisions when making investment decisions (Berg et al., 2019). The results of this study suggest that hospital administration regarding BDA technologies should better develop IT competencies, particularly in complex matters such as BDA technologies.

Leadership IT Capabilities

Clear jurisdictional boundaries are necessary between the CIO and the CEO. The authors Gerth and Peppard (2016) interviewed over 100 top digital executives, board members and surveyed approximately 700 CIOs globally. The authors investigated what causes CIO involuntary attrition and what can be done to alleviate the phenomenon. Similar to the prior study in which internal coordination was vital, Gerth and Peppard (2016) report that a clear jurisdictional boundary is necessary to construct a relationship strategy with top executives. Additionally, greater diversity in digital leadership roles has decreased CIO jurisdictional control (Magnusson et al., 2019). Nevertheless, these findings further support the notion that hospital administration must communicate a clear digital strategy and be conversant with BDA and digital technologies.

Translating BDA Into Business Value

The is little understanding of how to translate BDA into business value. Through the lens of complexity theory, the authors Mikalef et al. (2019) employ a mixed-methods approach investigating a sample of CIOs from Greek firms across three case studies. Complexity theory posits that organizations are adaptive systems that self-organize and evolve based on their environment (Mikalef et al., 2019). Mikalef et al. point to technical and managerial skills as a standard capability needed for the effective use of BDA. Further, the study highlights the challenge of acquiring the necessary resources to realize the value and the lack of a BDA strategy (Mikalef et al., 2019). Along this same line of reasoning, Božič and Dimovski (2019) showed generating business value from BDA should consider the interplay of organizational resources and its knowledge-creating capabilities. The data management process was also linked to creating value from big data (Zeng & Glaister, 2018). These studies underscore how effective use depends on management and technical capabilities and those same people's ability to articulate a clear BDA strategy to the organization. Although the former study did not address how firms acquire the needed capabilities through partnerships or absorbing BDA expertise, the study reinforces the notion that effective use of BDA requires hospital administration to consider managing its BDA resources.

Resource Allocation and Firm Performance From BDA

Similarly, Gravili et al. (2021) investigate the effects of intellectual capital and the role of BDA in healthcare organizational performance. The authors employed a mixed-methods approach to developing a measurable framework through a systematic literature review and statistical testing via publicly available data on hospitals from 28 European countries. The authors found that intellectual capital from BDA capabilities is more important for firm performance than physical assets in healthcare (Gravili et al., 2021). Firm performance is also linked to ambidexterity (ability to adjust using existing resources) and agility (Rialti et al., 2019). However, the findings of their study were inconclusive regarding the applicability of absorptive organizational strategies. The capabilities may be internally developed or acquired from external resources.

The link between firm performance and data quality remains unresolved. Wamba et al. (2019) investigated this link, finding that BDA resources and capabilities such as talent and information quality are determinants of firm performance while strategic alignment plays a moderating role. Wamba et al. (2019) sampled 150 business analysts and IT managers from a French market research firm using an online survey and RBV and IT quality theory lenses. Wamba et al. attempted to better understand the relationship between BDA quality and firm performance. These theories combined conceptualize firm performance in terms of its resources, competitive environment, perceived technological quality, information quality, and talent of BDA (Wamba et al., 2019). The results of their study suggest BDA intellectual capital and BDA resources are linked to firm performance. Further, internal integration has a moderating influence of BDA on performance (Chen & Chen, 2021). Finally, the results of these studies suggest BDA may have a positive impact on hospital operational performance.

Organizational Performance and BDA Temporality

The impact of temporality on the BDA business value is not well understood. Therefore, Conboy et al. (2020) investigated the link between BDA implementation speed and business value. Conboy et al. gathered interview data from two information systems teams to examine the problem through the lens of temporal theory. The results provide a basis to challenge the generally accepted assumption that the use of BDA increases the speed of activities as business value (Conboy et al., 2020).

Their study was limited in not including the perceptions of BDA end-users focusing on IT personnel only. Furthermore, the framework for their study was underdeveloped in that it merely focused on the practical temporal benefits of BDA implementations. The authors could have considered other time-relevant theories such as competitive dynamics as a lens that posits that organizations perceive opportunities given the current state of operations versus what could be done and take actions to exploit the prospect (Bridoux et al., 2013). Nevertheless, the results of their study suggest hospital administration should also consider the temporality of BDA implementations in organizational design decisions.

Entrepreneurial Orientation and BDA Value

The reallocation of resources designed to create value from BDA in resource-starved environments is poorly understood. Zeng and Khan (2019) investigated how managers can orchestrate, bundle, and leverage resources from big data for value creation. Zeng and Khan (2019) utilized conceptual frameworks of resource management and entrepreneurial orientation to view the problem. Zeng and Khan (2019) used an inductive multi-case study of Chinese online firms to better understand the process of BDA value creation. The results of their research suggest that entrepreneurial orientation is vital through which companies based in emerging economies can create value from big data by bundling and orchestrating resources (Zeng & Khan, 2019). A Portuguese study of 938 companies across multiple industries also found similar results (Ferreira et al., 2019). The implications of their research suggest hospital administrators with an entrepreneurial orientation may be able to overcome the resource entry barrier to BDA. Furthermore, their findings may inform board or directors' CEO hiring decisions.

BDA Resource Allocation

BDA investments may affect firm performance. Suoniemi et al. (2020) performed an empirical study of U.S. publicly traded firms investigating how BDA investments affect firm performance. Suoniemi et al. viewed the problem through the lens of resource based view, which assumes firms will apply their resources toward the objective of competitive differentiation. Sample selection focused on firms with greater than 1000 employees as the barrier to BDA entry can be significant. The authors gathered primary data via a survey of 301 senior marketing executives and analyzed it via structured equation modeling. Their research revealed that leadership directing resources toward enhancing BDA capabilities improves performance through enhanced market-directed capabilities. Furthermore, according to Suoniemi et al., firms pursuing a differentiation rather than cost-leadership strategy gain the most from big data resource investment. Torres et al. (2018) arrived at similar conclusions revealing the effective use of BDA was linked to improved performance moderated by a firm's change capabilities.

Homogeneity of BDA Resources for Improved Performance

The organizational actions that contribute to realizing value from BDA are mainly unknown. Dremel et al. (2020) investigated this problem via a revelatory case study of an automotive manufacturing company. Dremel et al. viewed the issue through affordance theory, which suggests that actors' perceptions or affordances must be perceived before actualizing or realizing value. The authors identified four affordances of enhancing, constructing, coordinating, and integrating. Dremel et al. also identify structural, actor-level, and technology-level realization mechanisms. The structural mechanisms resulting from the study emphasize organizational design elements that include digital officers, functional-specific analytics sub-units, and collaborative processes throughout the value chain (Dremel et al., 2020). Along this line of reasoning, BDA has been shown to mediate the relationship between digital technology orientation and operational performance (Yu et al., 2021). The findings from these studies are particularly relevant for hospital administration as they suggest BDA capabilities and resources should be placed throughout the hospital delivery model.

Role Configurations

Management scholarship is replete with studies regarding digital initiatives and transformations such as BDA. For instance, as mentioned earlier, the role of CDO is a relatively new phenomenon first emerged in 2003 (Kunisch et al., 2020). Since its emergence, there have been three threads of CDO and digital transformational research. First, explorations of the jurisdictional boundaries of CDO and other technology leadership. Second, the impact of CDO or digital transformations on operational, firm, and organizational performance. Lastly, studies on the effects of CDO and digital transformations on business value. The following section presents research on digitization initiatives such as BDA and the impacts of new roles and responsibilities configurations.

Professional Services Impacted by Digitization

Digitization is driving change in the professional services industry. Kronblad (2020b) investigated the professional services industry to understand better how digital transformation affects operating conditions. The author viewed the problem through a conceptual framework of business logic with the dimensions of high knowledge intensity, low capital intensity, and professionalized workforces. The study results suggest that digitization has an egalitarian effect on professional service firms. Specifically, knowledge intensity is inversely related to capital intensity, while workforce professionalization is decreased (Kronblad, 2020b). Similarly, digitization in professional service firms has proven to be a competitive differentiator (Kronblad, 2020a). These findings are significant for hospital administration, as they further affirm the resource barrier for BDA and show how firms with high intellectual capital can lower information asymmetries internally yet increase them externally.

Organizational Control

Digitization provides an opportunity to create new capabilities for monitoring organizational activities. Schafheitle et al. (2020) investigated the effect of digital transformations on organizational control mechanisms over incumbents. Schafheitle et al. used a multi-stage morphological analysis to understand the research problem, employing a qualitative approach, first gathering primary data via semistructured expert interviews, developing a framework, and testing the framework with two exemplar cases. Schafheitle et al. viewed the issue through configurational theory, which assumes various internal design elements emerge within organizations to respond to their external operating and market environment. Additionally, according to Schafheitle et al., control is the power management has over its constituents to affect the actions to achieve organizational objectives. Schafheitle et al. found that digital technologies, such as BDA, expand organizational control capabilities. Also, Schafheitle et al. recognized how organizational control mechanisms might alter the tasks of its leadership. Digital control mechanisms may also have negative impacts, such as improper use to create new power relationships, affecting interpersonal relationships (Palumbo, 2021). These results suggest that the expansion of control from BDA raises information asymmetries between hospital administration and subordinates. Furthermore, hospital administration should consider the asymmetries among employees as well.

The Role of CDO

The role of CDO is a new phenomenon across various industries charged with reducing information asymmetries among stakeholders caused by digitization efforts. The CDO role has been characterized as a digital accelerator, digital marketer, or digital harmonizer (Tumbas et al., 2017). Kunisch et al. (2020), in a recent exploratory empirical study, aimed to understand the determinants for its emergence better. Kunisch et al. gathered secondary data on firms listed in the Standard & Poor’s 1500 index between 2000 and 2018. Kunisch et al. characterized the role as either generalist or domain specialist. The results of their study suggest that broader strategic and structural factors, such as performance conditions and firm size, should be considered.

Furthermore, more specific factors, such as board characteristics and the presence of an incumbent CIO position, should also be considered (Kunisch et al., 2020). The results of their study suggest hospital CEOs considering a CDO role must factor existing resources, BOD characteristics, and other technological leadership positions into the decision process. Furthermore, existing resource configurations may inform necessary CDO antecedent qualities.

Information Asymmetries

The underlying premise of my study is that BDA creates an inherent information asymmetry between BDA experts and hospital administration that require actionable information in their decision-making processes. To restate the definition, *information asymmetry* is when one party has better, more actionable information than another (Bergh et al., 2019). Applying RDT, hospital administration will take a prescribed set of actions to reduce information asymmetries. The following section presents BDA literature regarding the phenomenon of information asymmetry.

Algorithmic Transparency Mitigates Adoption Resistance

Implementing BDA in healthcare may be resisted by physicians and caregivers. The authors Chen et al. (2020) aimed to investigate the mitigating factors of BDA adoption in healthcare institutions. Chen et al. conducted expert interviews with physicians, practitioners, medical staff, and scholars. They weighted the data using an analytic hierarchy process and processed the relationships using a programming technique that compares an ideal solution to the best alternative solutions. Chen et al. showed that the main barriers to medical big data applications are expertise, operation, and market access barriers. Therefore, by understanding the sequence of the importance of resistance factors, managers can formulate efficient strategies to solve problems with appropriate priorities (Chen et al., 2020). The results of their study are relevant to my study in that the expertise barrier alludes to physician and practitioner mistrust of information derived from big data.

Similarly, Fiske et al. (2019) contend making BDA algorithms transparent will reduce the barriers to their application in healthcare. Their results are further underscored in that BDA implementations must account for the sociotechnical healthcare system (Benda et al., 2020). In short, mistrust in BDA algorithms manifests as information asymmetry between providers and BDA experts.

Loss of Autonomy in Clinical Decision Making

Information asymmetry can also be viewed as a loss of autonomy for physicians and nurses. Wijnhoven and Koerkamp (2019) investigated the barriers to adopting clinical decision support systems (aka BDA). Wijnhoven and Koerkamp conducted a qualitative single case study with primary data from expert interviews with a case organization in the Netherlands. Wijnhoven and Koerkamp found two key barriers relevant to my research. First, clinical users of BDA found the loss of autonomy a barrier, alluding to the IT department as too disconnected from clinical practice. Second, clinical users suggested possible ethical issues leaving clinical decisions to IT personnel (Wijnhoven & Koerkamp, 2019). Similarly, other findings point to the lack of human supervision in automated systems as the root of clinician skepticism (Mehta & Pandit, 2018). The above results suggest that information asymmetries between BDA experts and clinical staff are a significant factor in adoption resistance.

Knowledge Sharing to Reduce Information Asymmetries

Knowledge sharing mitigates information asymmetries among stakeholders. Dasí et al. (2017) investigated knowledge sharing in multinational corporations through the lens of knowledge-based theory, which suggests organizations can develop differentiating knowledge-sharing capabilities. Dasí et al. indicate that extrinsic motivation, result-oriented values, and participation in corporate employee development are positively related to greater knowledge sharing. In addition, Dasí et al. hypothesized that employees inclined to share knowledge with other units would also share within their unit—Survey of over 1400 respondents in a Norwegian multinational corporation. Their findings suggest that interunit sharing typically occurs without organizational intervention, while extra-unit sharing may require organizational intervention (Dasí et al., 2017).

Moreover, a study of highly formalized organizations revealed a propensity for informal knowledge-sharing mechanisms to emerge over bureaucratic versions (Alshwayat et al., 2021). The results of these studies suggest interunit knowledge sharing is inherently less risky than outside the unit. Therefore, hospital administration should consider organizational design strategies that support knowledge sharing outside BDA expert functional units.

Communicating Perceived Usefulness to Improve BDA Adoption

The effects of BDA system characteristics on the attitude of leadership toward their use is a topic that may influence adoption decisions. The authors Verma et al. (2018) investigated the problem using a quantitative approach through the lens of the technology acceptance model. Verma et al. gathered survey data from 156 digital experts from companies in India. Verma et al. revealed that perceived usefulness and attitude mediate BDA adoption. Furthermore, BDA adoption in healthcare is moderated by resistance to change (Shahbaz et al., 2019). Gaining a deeper understanding of the factors affecting user attitudes toward BDA would be a valuable extension to their findings. Nevertheless, the results of their study suggest that hospital administration must manage the perceived usefulness of BDA from various user groups, which may indirectly impact information asymmetries between users and experts.

Competitive Relationship of Parent and Spinoff

Corporate investors perceive competitor benefits as they expect knowledge sharing when the spinoff is closely linked to the parent company's innovation capabilities (Bae & Lee, 2021). Their study was a quantitative analysis of secondary data and did not consider the real-life experiences of investors. The authors noted the limited generalizability of the results as the study focused on a single healthcare device company (Bae & Lee, 2021). Conversely, private equity consolidations in healthcare have shown to be a mechanism to reduce information asymmetries by pooling resources (Appelbaum & Batt, 2020). The findings of their study suggest that venture capital investors can influence the level of information symmetry of innovativeness between the parent and spin-off when the parent company and spin-off compete within the same market. More broadly, powerful external actors can function as an information asymmetry mitigating factor.

Competitive Intelligence and Information Asymmetry

Competitive intelligence is a capability that increases the information asymmetry between competitors. Competitive intelligence has emerged as a strategic capability, particularly with the growth in the volume of publicly available data from social media, text messages, blogs, and the internet. However, the link between competitive intelligence strategies and the effective use of BDA is not well understood. The authors Ranjan and Foropon (2021) investigated the mechanisms in which organizations incorporate BDA-driven competitive intelligence decision support into their business models. Ranjan and Foropon employed a grounded theory approach with an exploratory qualitative multi-case study method of three IT firms in India. The findings indicate a preference for a centralized informal process of competitive intelligence instead of a clear formal structure (Ranjan & Foropon, 2021). Research by Hoffman and Freyn (2019) confirms that BDA-enabled competitive intelligence will require new capabilities and tools. The results of the above studies suggest that competitive intelligence in a BDA-oriented organization may temporarily affect the centrality of BDA resources.

Additionally, BDA may have relevance as a strategic resource to augment rather than supplant traditional business models. Following this logic, hospital administration may consider BDA as a decision-support strategy in the CI space. Research by Y. Wang, Kung, et al. (2018) shows that decision support is a crucial path to value. Another healthcare study found a positive relationship between decision support capability and a hospital organization's information processing capability (Wetering, 2019). Moreover, BDA has also been shown to provide organizations a competitive advantage (Mikalef et al., 2020). These studies suggest hospital administration will need to invest in resources to develop new capabilities and acquire new tools in order to differentiate among its competitors.

Egalitarian Effect on Information Asymmetry

The healthcare delivery supply chain is a highly information asymmetric environment of buyers and sellers. However, little is known about how minorities and women manage the information asymmetry with large, powerful suppliers. The research of Lashley and Pollock (2020) shows how minority actors providing commodities use information from various sources in a healthcare supply chain to maintain a cognitive centrality to buyers to influence buying decisions. These results suggest the use of soft power in information asymmetric buyer-supplier relationships may have an impact (Lashley & Pollock, 2020). Along this same line of reasoning, democratic soft power leadership processes have been shown to be more successful in digital environments (Porfírio et al., 2021). These studies suggest BDA may have an egalitarian effect on hospital delivery models. As such, hospital administration should consider organizational design strategies that also consider the role of low power actors.

Summary and Conclusions

There are three themes evident in the BDA research outlined above. First, organizational configurations are context-dependent and may be absorptive, collaborative, autonomous, bridging, buffering, or boundary-spanning. Along this line of reasoning, BDA's effective use is linked to the sociotechnical healthcare system (Benda et al., 2020). Furthermore, some studies suggest that intellectual capital moderates absorptive organizational strategies (Kronblad, 2020b), while other studies found a link between BDA effective use and absorptive capacity (Siachou et al., 2021). The second theme is that resource availability predominantly drives strategies (Caesarius & Hohenthal, 2018). Furthermore, compelling evidence exists offering hospital administration should direct resources to promote the homogeneity of BDA capabilities throughout the organization (Dremel et al., 2020). The final theme is that BDA effective use is linked to an egalitarian effect on organizational intellectual capital (Lashley & Pollock, 2020). For instance, studies show democratic leadership processes are more effective in digital environments (Porfírio et al., 2021). To conclude the third theme, digital experts' antecedent organization resource configuration and hierarchical position moderate digital leadership behavior and style (Brass & Burkhardt, 1993).

As mentioned earlier, there is a lack of understanding of the conditions and circumstances that influence hospital administration to make organizational absorptive choices to reduce the information asymmetry with BDA implementations. This qualitative single case study explores the circumstances and conditions that influence absorptive organizational design choices of hospital administration to reduce information asymmetry caused by BDA implementation. I viewed the problem through RDT, which assumes hospital administration will reduce dependence on external resources. This study would help fill the literature gap to understand the link between BDA and organizational absorptive choices.

Chapter 3 is divided into three sections: research design and rationale. The second section is methodology. The third presents strategies to address issues of trustworthiness. That chapter concludes with a summary and transition to results in Chapter 4.

Chapter 3: Research Method

The purpose of this qualitative single case study is to explore the circumstances and conditions that influence absorptive organizational design choices of hospital administration to reduce information asymmetry caused by the implementation of healthcare BDA. Information asymmetry is emerging as a new challenge for BDA-oriented healthcare leadership as they operate within a highly regulated environment and must maintain control of sensitive patient data. This study focuses on the costly absorptive organizational design choices (e.g., hiring BDA experts, organization restructuring) hospital administration faces. The effective use of BDA requires a paradigm shift from compartmentalized group-controlled operations to a collaborative approach throughout the healthcare ecosystem (Nambiar et al., 2013). Hospital administration must balance these emerging collaborative requirements of BDA effective use against the healthcare ecosystem's regulatory and patient data protection requirements.

Chapter 3 contains the rationale for selecting a qualitative study research design, a description of my role as the researcher, an explanation of the research methodology, a discussion of trustworthiness issues, and an outline of the ethical procedures of this study. Finally, the last section presents a summary and transition to Chapter 4: Results.

Research Design and Rationale

The research question for this study was: How do the circumstances and conditions of information asymmetry caused by BDA influence the organizational design choices of hospital administration organizational? The central concepts of this study are information asymmetry and BDA. This study employs the definition of information asymmetry first posited by Akerlof (1978), in which one group or individual has more knowledge and superior, more actionable information than another. The latter concept, BDA, is defined as integrating and processing heterogeneous digital data with specialized tools to discover new relationships and actionable information (Ristevski & Chen, 2018).

I used a qualitative single critical case study method to answer the research question posed in this study, although quantitative and qualitative were both evaluated. Thus, the following sections present a progressively granular evaluation of the research design decision process, beginning with research traditions, then qualitative approaches, followed by case study design, and concluding with an argument for single case versus multiple case study design.

Research Tradition Rationale

Whereas the quantitative design assumes the independent and dependent variables regarding a phenomenon are measurable and can be statistically analyzed to yield generalizable results that explain their relationship (Ragab & Arisha, 2018; Yilmaz, 2013), qualitative inquiry is used when a complex issue affecting a group, population, or individual needs to be better understood. The qualitative research approach is well-suited for investigating emergent phenomena as it encompasses a range of interpretive techniques that can yield a deep understanding of a phenomenon (Birkinshaw et al., 2011). Typically the qualitative tradition is used as a basis to identify variables that can later be measured and quantitatively studied (Creswell, 2007). Morgan and Smircich (1980) admitted that quantitative design is dominant in management science but suggested that its core assumption is rigid and that human beings are social actors, not merely responding to a phenomenon concretely.

Further, human beings may contribute to creating the social world surrounding a phenomenon. However, the nascence and lack of measurable variables regarding the BDA phenomenon in healthcare invalidate the core assumption of the quantitative approach. As such, the qualitative tradition was most appropriate for the research question in this study.

Before proceeding to the following evaluation of the various qualitative approaches, it is essential to consider the type and nature of the research question rather than simply the core concepts described earlier. First, the research question is exploratory as it asks how to suggest a qualitative approach (Sandberg & Alvesson, 2011). Second, the objective is to understand how hospital administration's real-life conditions and circumstances influence organizational decisions. The aim is not to understand the lived experiences that influence organizational design absorptive decisions of hospital administrators. Outlined below, the distinction between real-life conditions and circumstances versus lived experiences is essential when determining the type of qualitative approach. Also, the object of the study is a group of hospital administrations, not idiographic. Finally, the object of the study indicates the appropriate qualitative design selection. The following paragraphs present an evaluation of each of the five qualitative approaches for this study.

Qualitative Approach Rationale

As stated earlier, the research tradition for this study is qualitative, and the specific research design is a critical single case study with embedded units design.

Narrative Inquiry

The narrative inquiry would not have been appropriate for this study. Narrative inquiry attempts to understand individuals' lived and told experiences regarding a specific event compared to the facts of the event (Franzosi, 1998; Moen, 2006). This study aimed to understand better the conditions and circumstances of the information asymmetry caused by BDA, not the participants' lived experiences.

Ethnography

The ethnographic approach would not have been appropriate for this study. Ethnography requires the researcher to be actively involved or practice the phenomenon under investigation to understand the subjects' lived experiences (Simmons & Smith, 2019). My involvement in the phenomenon as the research was not feasible as this study investigated how hospital administration mitigated the past phenomenon of information asymmetry.

Phenomenological

The objective of phenomenological inquiry is to derive meaning from the lived experiences of several subjects regarding a specific concept or phenomenon (Chan et al., 2013). Phenomenology would not have been appropriate because the objective of this study was not to derive the meaning of the organizational design choices but, instead, to understand the circumstances and conditions that led to those choices.

Grounded Theory

The grounded theory extends narrative and phenomenological inquiry toward generating a thesis or a process model of the phenomena from data gathered from participants who have experienced the phenomenon (Starks & Trinidad, 2007). However, grounded theory would not have been appropriate for this study as my objective was to test the boundaries of a well-established theory in a new context.

Case Study

I elected to use the case study method for two reasons. First, the case study method aims to understand a context-sensitive phenomenon by analyzing data from multiple sources and various perspectives (Rashid et al., 2019). Thus, I evaluated primary data from participants and secondary data from online and grey literature to ascertain the conditions and circumstances leading to organizational design choices. Secondly, the phenomenon is viewed through its naturally occurring context, assuming context influences the phenomenon (Rashid et al., 2019). Thus, in this study, I investigated the phenomenon in a new, unstudied context: healthcare.

Case Study Research Rationale

Again, the research question for this study is: How do the circumstances and conditions of information asymmetry caused by BDA affect hospital administration organizational design absorptive choices? According to Yin (2018), there are five rationales for a single-case study. As stated earlier, I employed a qualitative single critical case study with an embedded unit design.

Critical Case Rationale

The critical case approach was selected because, according to Yin (2018), the central rationale for this type of study is to evaluate a case against a theoretical framework with clear propositions such as RDT. As outlined in Chapter 1, the theoretical significance of this study was to test RDT within a hospital context. Unusual, revelatory, common, and longitudinal were ruled out as appropriate case study designs. First, according to Yin (2018), an unusual case assumes a deviation in theoretical norms, whereas a revelatory case method is when a previously unavailable or inaccessible situation becomes available. Neither revelatory nor unusual cases would have been appropriate for this study as they assume an a-priori understanding of the organizational design choices made by hospital administration. The common case approach assumes a single case represents a more extensive set of cases, which is impossible given the lack of understanding of the conditions and circumstances leading to organizational design choices in a hospital context (Seawright & Gerring, 2008). Lastly, the longitudinal case was not appropriate as it involves studying a phenomenon at multiple time points. The research question for this study lacks temporal elements.

Single Embedded Unit vs Multiple-Case Study

As outlined above, I employed a single critical case study with multiple embedded units approach over a multicase approach. Multiple case study assumes a common phenomenon, characteristic, or condition across a collection of case organizations (Stake, 2013). Single case studies provide conceptual context for unexplored phenomena, such as BDA, and reveal new avenues of research (Boddy, 2016). The multicase study design would not have been appropriate as the objective of this study was to fill a research gap on the absorptive choices of hospital administration and, therefore, not feasible to identify a common phenomenon across multiple organizations.

According to Yin (2018), there are two single case study types, holistic and multiple embedded units. Multiple embedded units help promote study focus versus a holistic approach that lacks the necessary specificity but may be used when subunits are not readily identifiable (Yin, 2018). Identifying embedded units should be feasible as hospital organizational structure is complex, with various interrelated actors and functional groups (Fiorio et al., 2018). The approach of multiple embedded interrelated functional groups is based on Hopkins and Hawking (2018), investigating the use of BDA in the supply chain. Additionally, the general organizational design is relatively consistent across hospitals which should support the transferability which will be discussed in greater detail later in this chapter.

In summary, the qualitative research tradition was employed due to the emergent phenomenon of information asymmetry associated with BDA implementations. A critical case is appropriate as the research problem is viewed through the lens of RDT and the objective is to test the boundary conditions of RDT in a hospital context. A single case approach over the multicase approach was used as it is infeasible to identify multiple case organizations experiencing the same conditions and circumstances. Lastly, multiple embedded units were studied as the hospital ecosystem is complex, with various interrelated units.

Role of the Researcher

In qualitative research, the researcher is an integral part of the research design (Creswell & Poth, 2007). As the sole researcher, I was directly involved in conducting the interviews and all aspects of the data collection process. I have no authority over the participants in the study or financial influence. I have worked in the health care field for over 20 years and have witnessed first-hand the phenomenon in this study. In addition, my professional role in research administration affords me access to big data, analytics, and AI experts.

Additionally, my research philosophy has post-positivist leanings. Post-positivists view the processing of understanding as a theoretical exercise in which theories are tested and boundary conditions refined in various contexts (Allmendinger, 2002). Post-positivists place a heavy burden on research methods and design to ensure validity and reliability. Moreover, they borrow heavily from the scientific method (Tekin & Kotaman, 2013). They typically begin with a tested theoretical framework as a basis for the inquiry, as evidenced by my use of RDT as a lens to view the phenomenon of information asymmetry (Creswell, 2014).

Methodology

Research methodology is a statement of work or plan of action to arrive at the results (Crotty, 1998). In this Methodology section, I describe the participant selection logic, instrumentation, recruitment procedures, participation procedures, data collection process, and data analysis plan.

Participant Selection Logic

Establishing case selection criteria is an essential consideration in qualitative research, especially given the nascence of the phenomena. The results of this case study ultimately rely on the selection criteria (Herron & Quinn, 2016). Furthermore, using explicit inclusion and exclusion criteria helps focus on relevant cases (Patton, 1990).

Case Selection Criteria

Case selection was conducted from a population of online and gray literature published use cases. The case organization was a U.S. hospital. Non-U.S. hospitals were excluded for two reasons. First, as mentioned in Chapter 1, United States spends more per capita than any other country, suggesting that BDA's operational and financial improvements would have the most significant impact. Second, non-U.S. hospitals have a different operating model, and are typically publicly funded, while U.S. hospitals are predominantly privately owned and operated.

Case selection was conducted from a population of online and gray literature published use cases. Borrowing from Y. Wang, Kung, and Byrd (2018), case selection criteria included (a) that the case organization presents an actual BDA implementation platform or initiative and (b) that a change in organizational design was implemented by hospital administration.

Participant Selection Criteria

Based on the work of Singh et al. (2019), I began participant selection with C-suite leadership as they have the most influence over organizational design choices to mitigate information asymmetries. I excluded individual contributor roles as they likely do not have the authority to influence the organization's policy. Snowball sampling was used to ensure the most relevant individuals are participants (Singh et al., 2019). I planned to interview a population of 12 participants, or more if necessary to achieve thematic saturation. This estimated sample size was based on the work of Guest et al. (2006), which assumes a relatively homogeneous group of participants. Additional data from secondary sources were also gathered and analyzed to support thematic saturation.

Instrumentation

Data from primary and secondary sources were gathered to generate contextual conditions regarding real-world cases from ongoing and historical data sources (Easton, 2010; Yin, 2018).

Table **3** provides a list of possible data sources and the rationale for its acquisition. Semistructured interviews with BDA experts and hospital administration are the primary data sources (see Appendix C).

Qualitative research “requires a whole new way of thinking about what counts as evidence” (Xu & Storr, 2012, p. 1). According to Poggenpoel and Myburgh (2003), the researcher can be one of the biggest threats to trustworthiness in qualitative research. For instance, the researcher must be considered an instrument, especially when gathering primary data through semistructured interviews (Creswell & Poth, 2007). I employed reflexivity, member checking, and verbatim transcription to mitigate my influence, which will be detailed later.

Procedures for Recruitment

This study aims to determine the conditions and circumstances influencing hospital administration absorptive organizational design decisions from BDA. The target case organization is a U.S. hospital that has implemented BDA and made organizational changes. The target participants are hospital administration and BDA experts.

I reviewed secondary data to determine candidate organizations that meet the case selection criteria. Then, based on predetermined criteria, I placed each organization into a high or low category. Organizations meeting all the below criteria were categorized as high, and those meeting only one measure were placed in the low category:

- published case study peer-reviewed or other referencing a data transformation or BDA project

- a press release or other announcement stating they have hired or appointed a role with the title or responsibility includes the term “Data”
- a press release or other announcement stating a new group has been formed to manage data or digital data

Procedures for Participation

Secondary data of organizations in the high category were reviewed to identify the contact information for the CEO of the hospital. A phone call, email, or letter was then sent asking whether the CEO would be interested in participating in the study and if I could contact them to discuss the details. I excluded the organization if there was no response within 14 days of the request. Positive responses from CEOs were approached according to their preferred method of communication.

I asked for a point of contact to help coordinate the study from the case organization if there were no issues or barriers to performing the study determined during the follow-up call with the CEO. After identifying the initial participants, I emailed each potential participant the study invitation. I removed potential participants from the study if there was no response after 7 days or if they declined the invitation. Once I received confirmation of their acceptance from participating, I sent the informed consent and, if required, the de-identified data-use agreement (see Appendix C) for their approval. Once both documents were signed and returned, I sent the open-ended interview guide and scheduled the interview.

Data Collection

This section and the following data analysis sections borrow in part from the case study guide posited by Rashid et al. (2019), particularly the empirical material interpretation process. First, I collected primary data, as shown in

Table **3**, via interviews using Microsoft Teams communication software. Next, the interviews were recorded and initially transcribed using Dragon Naturally Speaking voice recognition software (https://www.dragons-stores.us). If there were not enough recruits to participate in the interview to reach thematic saturation, I would remove the case organization from the study and restart the recruitment procedure. I then verified the automated transcription and transferred it into a Microsoft Word document. Then, I imported it into NVivo for coding. Next, I collected secondary data as shown in

Table **3** and imported them into NVivo software for coding. Finally, I will store all digital data in an encrypted format, and paper records will be held in a locked cabinet, accessible only to myself.

During the interview, I made participants aware of the augmented member check process outlined in the interview guide (see Appendix A). I also reinforced during the interview that their privacy would always be maintained, and that they may leave the study at any time.

Table 3

Data Sources and Rationale

Data source	Description	Rationale	Frequency
Primary	12 semistructured interviews of IT personnel, healthcare administration, BDA users, BDA curators, and BDA experts in the case organization	This would be main source of data for thematic evaluation	Maximum 30-min interview
	Reflexive journal	Researcher as instrument	Before and after each interview
	Augmented member checks	Validation and verification of interview transcript	Second collaborative session with each participant
Secondary	Hospital organizational documents such as financial reports	Financial reports may provide strategic information on prior and future plans	After interviews to triangulate with primary data
	Hospital press releases	Press releases are good sources of information on success stories and absorptive organizational strategies (e.g., hiring a CDO from outside the organization or promoting from within	Before and after interviews to triangulate data
	Organizational announcements	Provides background information on corporate design strategies	After interviews
	Hospital internet page	Good source of information on organizational design strategies and BDA use cases as criterion sampling	Before and after interviews to triangulate
	Marketing databases (e.g., Definitive Healthcare)	Good source of financial information, job titles, employee background, and organizational statistics	Before interviews for background information and potential participant contact information

Note. IT = information technology; BDA = Big Data analysis; CDO = chief digital officer.

Data Analysis Plan

I performed data analysis using the logic model analytic approach for four reasons. First, it is well-suited for research on organizational change (Funnell & Rogers, 2011). Secondly, the logic model analytical technique is appropriate for this study as it is intended to describe how a specific set of intervention results in a set of specific outcomes (Funnell & Rogers, 2011). Third, according to Yin (2018) the logic model process is designed to match observed events to the theoretically predicted events of the RDT framework of this study. Lastly, the logic model analysis technique operationalizes a complex chain of events over an extended time to illustrate how a complex activity took place (Funnell & Rogers, 2011).

Coding

I performed pre-coding to refine and identify possible new sub-codes. For the initial data coding, I employed the theoretical coding method (Saldaña, 2015). According to Onwuegbuzie et al. (Onwuegbuzie et al., 2016) the constructs of the theoretical coding method are derived from the literature review. Initial criteria for the theoretical coding method are based on RDT, which suggests that organizations will undertake actions to reduce reliance on external resources (Hillman et al., 2009). Thematic and concept code definitions are based on prescribed activities of RDT (see Appendix B).

The in-vivo coding approach was also considered, which involves deriving codes from verbatim transcripts (Saldaña, 2015). However, many key terms such as big data, valuation, and AI within this study lack consensus definitions among scholars (Ylijoki et al., 2019). Therefore, during the interview, I asked each participant to describe BDA to address this tension. As such, it would likely be challenging to reach thematic saturation using the in-vivo coding approach.

Analysis

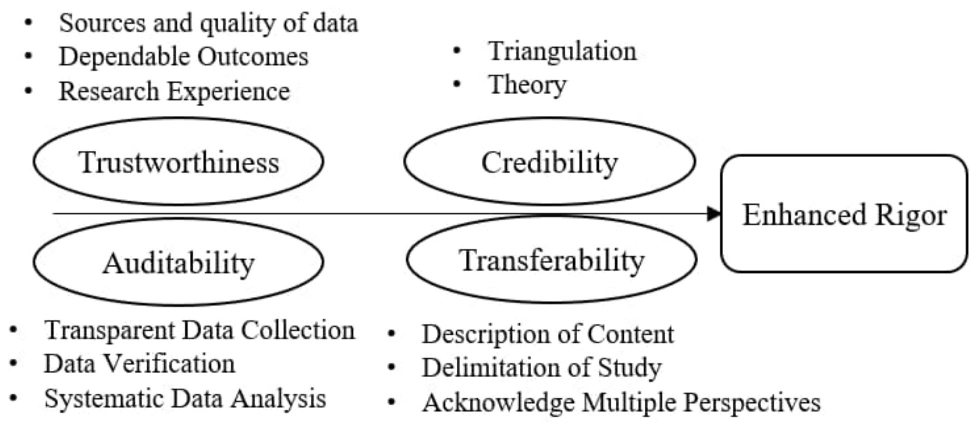
As mentioned earlier, I utilized a systematic approach in the data analysis process, as Rashid et al. (2019) suggested. Also, I employed multiple techniques for data analysis which, according to Lauri (2011) is a "Triangulation of data analysis." To conduct the analysis, I used NVivo (Version 12), qualitative data analysis (QDA) software, to organize the data. I read the primary and secondary data multiple times. First, in an unstructured manner, to get closer to the data focused on the research question (Ravitch & Carl, 2015). The second reading was more goal-oriented toward thematic resolution employing the theoretical coding approach. The data analysis process involved memo writing before, during, and after each interview. The memos included journals, reflections about informant participation (e.g., tone, attitude, comments), and redefining codes and sub-codes (Ravitch & Carl, 2015). Data analysis triangulation was also be employed using hypothesis coding and content analysis (Lauri, 2011). Finally, I excluded primary data from participant interviews that do not match any of the codes in Appendix B.

Issues of Trustworthiness

Trustworthiness in qualitative research provides a framework for which others can evaluate the value of an investigation to their paradigm (Stahl & King, 2020). To improve trustworthiness, the design of this study borrows from the TACT model of trustworthiness shown in Figure 5. The TACT model includes the four dimensions of trust, auditability, credibility, and transferability (Daniel, 2019). Also, to improve trustworthiness and to help communicate the research approach, this study borrowed from Cloutier and Ravasi (2021) and utilized tables to display information where possible. Four dimensions of trustworthiness are outlined in the following paragraphs: credibility, transferability, dependability, and confirmability (Creswell, 2014).

Figure 5

TACT Model for Qualitative Research



Credibility

Credibility in qualitative inquiry is equivalent to the concept of internal validity in quantitative studies. To establish credibility, I employed several strategies in the design of this study. First, the research design was viewed through the lens of RDT, which is often used in organizational design studies which supports the verifiability of the results. Second, only findings from peer-reviewed journal articles were used in the analysis. Third, the triangulation of secondary data to primary interview data provides a richer case description (Zeng & Glaister, 2018). Third, I included multiple participants in the study to mitigate informant bias.

Furthermore, encouraging truthfulness by ensuring participant confidentiality also addresses informant bias (Singh et al., 2019). Forth, borrowing from Wehrens et al.'s (2020) study of BDA adoption, I performed member checks. Worth noting there is limited evidence that member checks improve findings in theory development such as this study (Thomas, 2017). I borrowed from Chase's (2017) augmented member check strategy for three reasons—first, the nascence of BDA in healthcare. Second, I used a single-case study approach, and third I am the sole researcher. The augmented member check included a second collaborative session with each participant to expand their input and offer more description. Lastly, I maintained a reflexive journal to capture my thoughts, feelings, and perspectives providing a reference to re-examine my positions that may influence the research design process (Chan et al., 2013).

Transferability

Transferability in qualitative inquiry concerns external validity, which is analogous to generalizability in quantitative research. Furthermore, according to Stahl and King (2020), qualitative inquiry expands understanding by transferring findings from one context to another. There are three strategies in this research design that support transferability.

First, I will employ a systematic literature review method (Grant & Booth, 2009). Second, a single critical case with multiple embedded functional groups was selected as embedded units to support transferability (Singh et al., 2019). Third, the strategy of enhanced or augmented member checks instead of traditional member checks, described above, will contribute to a richer description of the BDA phenomena on organizational design. Furthermore, according to Stahl and King (2020), providing a detailed context of the case organization promotes transferability. In the research setting of Chapter 4, I will include a precise context of the case organization, participants, method, and timeframe for collecting data. Lastly, to promote transferability, I will ensure the recruitment of participants are based on their expert knowledge of the BDA phenomenon (Daniel, 2019)

Dependability

Dependability is an element of trustworthiness, see Figure 5, in qualitative inquiry and refers to the reliability of the study's findings (Yin, 2018). I will employ four strategies to enforce this dimension. First, I will record and verbatim transcribe the interviews. Second, I will also utilize the practice of reflexive auditing to monitor the influence of my biases and assumptions on the study (Stahl & King, 2020). Third, borrowing from Conboy et al. (2020), I will use an audit trail from the data collection process to guide the formulation of conclusions. Finally, I will use elements from the physical and intellectual audit guide that Carcary (2020) posited, as outlined in Table 4.

Table 4

Physical and Intellectual Audit Trail Guide

Physical audit trail	Intellectual audit trail
Research problem identification and proposal development -	Clarification of philosophical stance
Literature review	Consideration of alternatives for evidence collection and data analysis
Research framework definition	Evidence interpretation
Sample selection	
Evidence/raw data collection	
Evidence management and analysis	
Artifact development	

Lastly, I utilized the principle of triangulation. First, primary data collection will occur via semistructured interviews with experts. Second, secondary data collection will occur from multiple sources. Finally, as outlined above, data analysis triangulation will also be employed using hypothesis coding and content analysis (Lauri, 2011). These analysis strategies combined will promote dependability.

Confirmability

Confirmability, not specifically present in the TACT model (Figure 5), refers to the level of neutrality in the study findings (Yin, 2018). This study employed four strategies to promote confirmability. First, as described above, a physical and intellectual audit trail was kept maintaining neutrality which is analogous to auditing in Figure 5. Second, borrowing from the phenomenological qualitative inquiry approach, I employed the self-reflective bracketing process to acknowledge my knowledge and assumptions regarding the phenomena (Chan et al., 2013). Third, like bracketing, I used reflexive auditing (Stahl & King, 2020). Lastly, the data analysis will utilize hypothesis coding based on the RDT as a framework that encourages objectivity in the study (Saldaña, 2015).

Ethical Procedures

Ethics in research is a spectrum of practices that address the trustworthiness outlined above and cover legal issues, intellectual property, responsible publication, and human subject protections. The following paragraphs summarize the ethical procedures for this study.

Human Subject Protections

The treatment of human subjects is paramount in research. Research must be performed scientifically, ethically, and according to all applicable regulations. Furthermore, studies must be designed and conducted to meet several requirements. First, the researcher must ensure compliance with confidentiality agreements. Second, the study results must not be misrepresented. Third, participants must not be deceived, or informed consent ignored. Lastly, all liability risks must be minimized (Burian et al., 2010).

To ensure all procedures are ethical, the Institutional Review Board (IRB) was consulted need to review and grant permission to perform the study (approval 12-23-21-0649351). I sent a study invitation to each participant. The invitation included an overview of the procedures, including follow-up activities and the purpose of the research. In addition, each participant signed the informed consent. The informed consent stressed that participation is voluntary and that they can withdraw at any time. All reports provided to participants during the enhanced member-checking process included pseudonyms to ensure anonymity.

Case-Organization Procedures

I masked the name of the case organization throughout the study. If required by the case organization, additional documentation or permissions were gathered. These requirements were identified and incorporated into the research design. If needed for the case organization, I established a de-identified data use agreement (DUA) (see Appendix C) with the case organization. The DUA allows the case organization to provide records to me.

Data Protection Procedures

Data collection was primarily gathered via recorded open-ended interviews with participants. I stored primary and secondary data in encrypted digital format, password-protected, and only accessible to me. I kept all paper copies of participant data in a locked cabinet to which only I have access. I destroyed all paper and digital data once the study was concluded.

Participant Relationship

This study did not involve any participant incentives. The case organization employed the participants, and I had no working relationship with them. Furthermore, I had no authority over the participants personally or professionally.

Responsible Research

I borrowed from Gastel (2015), who suggests using a checklist to promote responsible research, a regimented self-editing strategy. Lastly, I refrained from self-plagiarism by properly referencing all my prior work (Broome, 2004).

Summary

In this chapter, I discussed the research design focused on the research question for this study: How do the circumstances and conditions of information asymmetry caused by BDA influence the organizational design absorptive choices of hospital administration? Following the qualitative research tradition, a rationale was presented to answer the research question and reasoning for employing a single critical case study method with embedded units. My role as the sole researcher and my relationship with the healthcare industry were described. In addition, my post-positivists philosophical leanings were detailed as well as the associated core research assumptions. An outline of the criteria for case selection of a U.S. hospital and participant selection rationale was presented, which focuses on C-suite leadership as an entry point and snowball sampling. Strategies for improving trustworthiness were discussed, and lastly, ethical procedures were outlined.

Next, in Chapter 4, I present the results of the study. Chapter 4 will begin with a review of the study's purpose and research questions. Furthermore, it includes a review of the data collection method, the coding of the results, and a discussion of this study’s impact on management scholarship.

Chapter 4: Results

Although the relationship between BDA organizational, firm, and financial performance is well supported, scholars have paid little attention in the extant research to exploring the organizational design issues resulting from BDA (Al-Badi et al., 2018; Bergh et al., 2019; Mandlik & Kadirov, 2018). Absorptive organizational design choices include acquisitions, mergers, reorganization, executive changes, BOD adjustments, or new hires. BDA is a nascent, highly technical capability that generates information asymmetry between leadership who need actionable information and the BDA experts capable of developing it. The phenomenon is particularly acute in healthcare as the delivery, diagnosis, and treatment become more evidence-based, personalized, and data-centric. This qualitative single case study aimed to explore the circumstances and conditions influencing hospital administration organizational design absorptive choices to reduce information asymmetry caused by BDA. This organizational design problem was viewed through Pfeifer and Salancik's RDT. The research question of this study focused on the circumstances and conditions of information asymmetry caused by BDA that affect hospital administration organizational design absorptive choices.

This chapter is divided into six sections concluding with a summary of the results. The first section, Research Setting, includes factors influencing participant experience or interpretation of the study results. The second section covers participant demographics. The third section, Data Collection, contains variations from the plan outlined in Chapter 3 and any unusual circumstances encountered in the data collection. The fourth section, Data Analysis, provides for the reporting process, particularly the categories and themes that emerged. The fifth section covers evidence of trustworthiness, followed by the sixth section addressing the research results aligned with the research question with support for each finding. Finally, this chapter concludes with a summary of answers to the research question.

Research Setting

The 12 participants in the study were from a single case organization. The case organization was a private, not-for-profit regional health care system located in the Mid-Atlantic region of the United States. All the interviews were conducted and recorded via the Microsoft Teams communications service. All interviews were performed according to the open-ended interview guide (see Appendix A). All participants were engaging and provided rich responses during the interview. Table 5 provides a demographic overview of the 12 participants, and the following paragraphs offer statistical details. Of note, no changes in strategic direction, personnel, budget, or other organizational developments influenced the results.

Case Organization Description

The case organization leadership employs an organic strategy to address BDA resources and capabilities gaps. The organic design evolves as business, and clinical demand emerges and is not driven by an overarching IT strategy. During this study, BDA was used to develop population health management capabilities. Population health management addresses the health outcomes and distribution of outcomes to a group (Kruse et al., 2018).

Case organization leadership has engaged in multiple BDA initiatives since 2001 with varying success. The most recent initiative began in 2010 to incorporate BDA into the operational paradigm revolving around a centralized data warehouse. The data warehouse consolidates patient healthcare and financial data into a central repository managed by the IT organization. Organizational leadership has established data analytics roles within the high-patient volume departmental functions (e.g., emergency services, surgery services) and centralized data analytics functions within the IT group for lower-patient volume service areas (e.g., neurovascular services and pediatric services). The roles evolve based on business and clinical demand. During this study, the case organization employed a “hub and spoke” model in which cross-functional capabilities are centralized while operational-specific capabilities are embedded within the business units. Project-based virtual cross-functional groups are established to address emerging complex data analytics needs and disbanded once goals are achieved.

Demographics

The demographic information in this section is described from a resource and capabilities perspective (see Table 5). *Resources*, within the context of this study, are defined as assets used by the case organization to achieve its strategies, whereas *capabilities* are a subset of resources representing embedded, non-transferable skills and talent used to improve other resources’ productivity (Akter et al., 2016).

The sample size of 12 participants established thematic saturation aligned with the study objectives and goals and sufficiently answered the research questions. All 12 participants held senior leadership positions and were members of hospital administration at the case organization. Most (75%, $n = 9$) of the participants transitioned into their roles from within the case organization. Some (25%, $n = 3$) of the participants were hired from outside the case organization, two of whom were from academic backgrounds. Most participants (66%, $n = 4$) have held their current position for less than 5 years. However, most participants (83%, $n = 10$) were employed by the case organization for more than 5 years, and one was with the organization for 25 years. Most (66%, $n = 8$) of the participants hold terminal degrees, whereas all the participants hold at least a master's degree. Only a few (17%, $n = 2$) of the participants have technical backgrounds.

Table 5

Participant Demographics

Title	Participant	Years in current role	Transitioned to current role	Years employed with case organization	Background	Credentials
Chief operating officer	V01	<5	Inside	>20	Industry	MSN
Administrative director of clinical analytics	V02	>5	Inside	>5	Healthcare	PhD
Chief digital and information officer	V03	>5	Outside	>5	Healthcare	MBA
Chief population health officer	V04	<5	Inside	>10	Healthcare	PhD
Corporate director [program]	V05	<5	Outside	<5	Academics	PhD
Director data informatics and analytics	V06	<5	Inside	>20	Technology	MD, PhD
Director population health research	V07	<5	Outside	<5	Academics	PhD
Executive director accountable care organization	V08	>5	Inside	>10	Healthcare	PhD
Vice president emergency services	V09	<5	Inside	>10	Healthcare	MBA
Chief virtual health officer	V10	<5	Inside	>20	Healthcare	D Ed.
Chief medical information officer	V11	>5	Inside	>10	Healthcare	MD, PhD
Director data acquisition and measurement	V12	<5	Inside	>5	Technology	MBA

Data Collection

There were a few phases in the data collection process, including identifying candidate case organizations, case organization IRB review, approval, and identifying and recruiting participants. There were two sources of data. Secondary data were gathered from internet-published press releases, the Definitive Healthcare marketing database, and publicly available financial reports, whereas primary data were gathered from interviews, augmented member checks, and reflexive journal. Unfortunately, case organization's internal documents were unavailable and were the only source from the proposed list in Table 3 not used.

Case Organization Identification

As described in Chapter 3, identifying candidate case organizations employed the evaluation of three criteria from publicly available information. The first was whether a published case study or announcement referenced a BDA project. The second was whether an announced new role included the term "data" and whether a statement of a new group was formed to manage data or digital data. Twenty-six candidate case organizations met at least one of the three criteria. Fifteen were categorized as low, meeting only one of the criteria, whereas six were classified as medium, meeting two of the criteria. Finally, five were categorized as high, meeting all three criteria.

Case Organization Recruitment

As described in Chapter 3, I identified the CEO for all candidate case organizations. The chief academic officer (CAO) was also identified, which deviated from the research design. I sent an email invitation to the CEO and CAO for candidate case organizations categorized as high and medium (n = 11). I received three positive responses (30%) from CAOs; one was from a case organization as high. I then conducted phone conferences with each CAO to discuss the research study in more detail. Each CAO stated that they would need to discuss their support for the study with hospital administration and there would likely be required reviews by their IRB or Conflict of Interest (COI) committees. Two of the three CAOs stated that the hospital administration was interested in participating in the study but needed to identify a study coordinator for support. Only one site identified a study coordinator willing to support the investigation.

Case Organization IRB Approval

The study coordinator introduced me to the chair of the IRB via email. The chair of the IRB requested a copy for review of Walden University's conditionally approved Informed Consent along with a copy of the Letter of Cooperation, a signed letter that their IRB requires no additional review, after I clarified that the employees of the case organization would not be assisting in the research or data analysis. Additionally, the head of research administration and scientific affairs provided the signed letter of cooperation.

Identifying and Recruiting Participants

The study coordinator identified 52 candidates as meeting the study's inclusion criteria. I emailed each potential participant the Participant Study Invitation. Fourteen (26.9%) positive responses were received. Before their scheduled interview, I emailed each volunteer a copy of the informed consent.

Open-Ended Interviews

Primary data collection occurred over 3 weeks in which 12 of the 14 volunteers participated in Microsoft Teams recorded meetings lasting approximately 30 minutes each. Participants responded with "I Consent" via email before each scheduled interview. One participant interview lasted 55 minutes, which was longer than the 30-minute scheduled time. Unfortunately, I could not coordinate an interview session with two volunteers due to scheduling conflicts and availability. During each interview, participants were asked to recommend additional people meeting the inclusion criteria (i.e., snowball sampling). All the names provided by participants were included in the initial 52 identified by the study coordinator. As such, the snowball sampling did not yield any new volunteers.

The video recordings were copied from Microsoft Teams onto a local password-protected laptop for transcription. The original recordings were then deleted from Microsoft Teams. I then manually transcribed the audio recordings into a Microsoft Word document using Dragon Naturally Speaking voice recognition software. Next, I imported the Microsoft Word document into NVivo qualitative data analysis software for subsequent data analysis.

Augmented Member Checks

Each of the 12 participants was sent via email the three primary themes derived from the interview and asked to provide feedback and corrections. Only six of the participants responded to the member check. None of the six disagreed with the themes.

However, one of the six respondents provided additional information not disclosed during the interview.

Reflexive Journaling

Reflexive journaling occurred after each interview capturing details regarding the interview environment, participant demeanor, snowball sampling recommendation, and my thoughts and impressions. This primary data source proved very beneficial to the data collection process. After the first interview, I included additional questions to the Open-Ended Interview guide (see Appendix A). Specific questions regarding resource allocation and the origins of their role are consistent with RDT. For instance, I added a question to ascertain whether the participant in their current role originated from within the organization or outside. If within the organization, was it from IT, clinical department, or another department. If the participant originated from outside the organization, was it from academia, industry, or healthcare. Additionally, a question was included as to whether a participant's current role is a net-new position or a restructuring of an existing position. These additional interview questions are designed to help answer this study's research question about the conditions and circumstances that influence organizational absorptive choices.

Secondary Data Collection

According to Lauri (2011), using data from various sources improves the validity of qualitative research. As listed in Table 3, secondary data from hospital press releases regarding new roles, hospital internet pages regarding data analytics programs, and marketing database Definitive Healthcare regarding curriculum vitae were gathered when available. Curriculum vitae data in Definitive Healthcare is typically compiled from online social media. As related to this study, curriculum vitae information is beneficial in ascertaining participant backgrounds not mentioned during interviews. I did not collect hospital financial reports or internal organizational announcements as the case organization restricted access to these data for business confidentiality reasons. Of note, no unusual circumstances were encountered during the secondary data collection process.

Variations in Data Collection

Data collection was conducted as planned, except for some modifications to the interview guide and the transcription process. First, I added a question about how the participant arrived at their current position. I also added a question as to whether the participant was hired from within or outside the organization. This additional question helped ascertain the origin of their role and capabilities as a resource. Also, I added a question regarding their background. More specifically, the question concerned whether the participant had academic, outside healthcare, clinical, or technical background. Again, adding this question helped identify how organizational leadership acquired its resources. Secondly, I moved questions regarding BDA capabilities to the beginning of the interview. Feedback in subsequent interviews regarding capabilities naturally led to input on organizational changes. Finally, I removed questions regarding gender, age, and ethnicity during the interviews.

I planned to transcribe automatically using Dragon Voice Recognition software. However, the voice recognition algorithm was inaccurate the majority of the time. I spent tremendous time and effort manually correcting and reformatting the output. It turned out to be much more efficient and accurate to listen to the interview with headphones in short increments and then dictate using Dragon Voice Recognition software into a microphone on a second computer. The data were then transferred to the primary computer and deleted from the second computer.

A few unusual circumstances occurred in the data collection process. Minor situations arose during one interview and the scheduling of the final interview. During the first interview, the participant experienced technical connectivity issues. The participant initially used their computer to connect via Microsoft Teams but switched to their mobile phone to improve the audio. Also, the final interview of the chief operating officer took place one week after the other interviews. The delay was attributed to scheduling difficulties.

Data Analysis

I imported all collected data into the NVivo (Version 1.6.1) software to prepare for the analysis. The data analysis plan outlined in Chapter 3 included a minimum of three readings of the data with a redefinition of codes, followed by hypothesis coding, concluding with triangulation of primary and secondary data. Unfortunately, the planned approach proved inadequate as the pre-coding lacked the necessary granularity to bridge the participant responses to the interview questions and the themes established in Appendix B.

To bridge this granular gap, I borrowed a hybrid approach from Robinson (2021) that included six data readings in a stepwise fashion. The first reading was unstructured as planned to get closer to the data. During the second reading, I sub-coded terms identified in the definitions section of Chapter 3, such as effective use, organization, and strategic interdependence. The third reading was to sub-code all activities focusing on the hypothetical activities predicted by RDT (see Table 6). The fourth reading was the theoretical coding phase, where activities and actions are related to acquiring and controlling an external resource. The fifth reading focused on aligning the codes with the research question of this study by applying and categorizing codes as a circumstance or condition. The final sixth reading was to group all the sub-codes into major and minor final codes. The following paragraphs provide specific coding examples of readings two through six of the data.

Pre-Code Definitions Phase 2

In the second reading, I applied sub-codes related to some of the terms identified in the definition section of Chapter 1. Examples include absorptive capacity, intellectual capacity, boundary spanning, bridging, buffering, organizational separation, and strategic interdependencies. This phase is designed to transform participant phrases and statements into the context of the study aligning with the background literature. Table 6 provides the definitions of some Phase 2 codes.

Table 6

Phase 2 Code Definitions

Phase 2 Code	Definition
Capability acquisition	When a person is hired to fill a gap in organizational capabilities
Physician leadership	When a physician or clinical expert is placed in a role that bridges between the clinical and technical personnel
Boundary spanning	When the organization is changed to create interdependence between actors or functional groups
Risk based contract	A reimbursement contract that is prospective and
Vendor delay	Contracted vendor with capabilities are not responsive
Resource buffering	When a resource is protected or cordoned off from other resources
Organizational separation	Clear delineation and reporting structures
Strategic interdependence	When the outcomes of one group is dependent on the input of another
Intellectual capacity	Capacity to absorb information and technologies
Capability follows demand	The capability is defined after the need reaches critical mass
Asymmetry between clinical and technical	Capability difference between two groups
Dispersed capability	Common functions are repeated throughout the organization.

Hypothetical Activity Coding Phase 3

In the third reading, I applied descriptive activity sub-codes related to hypothetical predicted actions such as “new role assignment”, “evolving role”, “new governance”, “net new technology resource”, “centralized resource”, and “capability development”. These descriptive activity codes serve to categorize participant phrases into resource and capability management actions.

Theoretical Coding Phase 4

The fourth reading I applied and grouped the hypothetical activity codes defined in Phase 3 according to RDT predicted activities. Phase 4 codes are outlined in Appendix D. As a review, Pfeiffer and Salnik's RDT predicts hospital administration will take specific actions to reduce the information asymmetry caused by implementing BDA into its operational paradigm. Information asymmetry is generated from the highly technical skills needed and specialized tools required to create BDA outputs and the special skills required to interpret the output. Also, it is presumed that hospital administration lacks the necessary resources to accomplish BDA as their primary mission is to diagnose and treat patients. As such, hospital administration will need to absorb or acquire resources. The following paragraphs summarize the data analysis grouped by the predicted activities of RDT.

Interview Questions Phase 5

In this data analysis phase, the codes align the interview question responses with the theoretical framework and the hypothetically predicted activities (see Table 7). For instance, a participant responded to a question about management changes with "our new Chief Digital & Information Officer came from outside the company with a load of experience in digital technologies" would be coded as "Hire External Management".

Table 7

Interview Question Topics Tabulated with Hypothesis Codes

Interview question topics	Hypothesis	Codes
Influences to adopt BDA in general	Reduce the influence of external resources on internal BDA capabilities	Capability Development or Capability Acquisition or Transitory Capability Augmentation or Bridging Capability
Organizational changes in general	Reorganize organizational interdependence to reduce reliance on external resources	Restructure or Realignment or Resource Reallocation
Management changes	Hire new management with BDA skills to reduce reliance on external resources	Hire External Management or Develop Internal Management
Intra-organizational changes	Redesign organizational structure to increase dominance over external resource	Restructure for Dominance
Changes in BOD	Modify BOD makeup or BOD interlocks to reduce reliance on external resources	BOD Interlock or BOD Makeup or BOD Restructure
External partnerships	Establish interdependence with BDA partners to increase dominance	Joint Venture or Collaboration or Partnership Formal or Partnership Informal
Needed BDA capabilities	Actively evaluate BDA capabilities	AI or Machine Learning or Engineering or Regression Analysis
Management actions to address capability gaps	Hire, acquire, or create access to new experts in BDA	Capability Development Internal or Capability Acquire External

Major and Minor Codes Phase 6

In the final phase of the data analysis, the major and minor codes were assigned. Borrowing from Robinson (2021), these major and minor codes emerged over the first five readings of the data through an inductive process. Table 8 summarizes Phase 6 major codes and provides some logic as to when they are assigned. Table 9 summarizes the minor codes and when they are given.

Table 8

Major Codes Phase 6

Major code	Description
Culture	The beliefs and behaviors that determine how employees manage and conduct business
Communication	The process of sharing information between people within the workplace
Strategy	Plan of action to achieve the vision and mission of the organization

Table 9

Minor Codes Phase 6

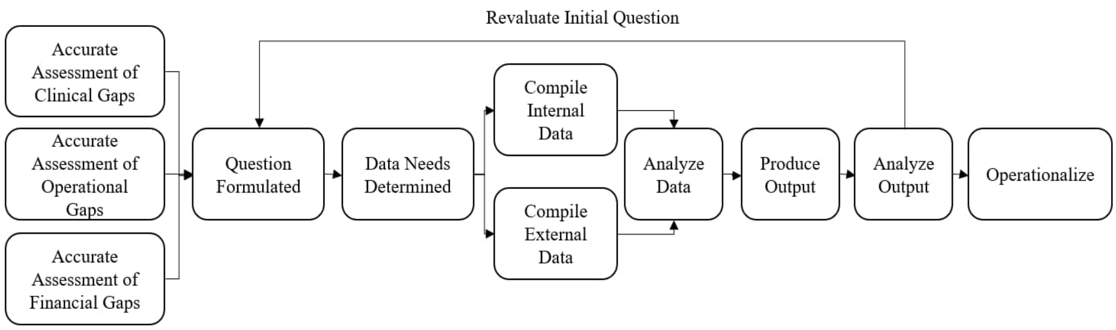
Minor code	Description
Prospective reimbursement models	When population health, risk based contract, value based contracts, or similar
Poorly formulated BDA questions	When problems are not clearly articulated
Evolving BDA demands	When requests for BDA information rapidly changes or is requested from new or different actors within the organization
Intellectual capacity gap	When organizational actors lack the know-how, motivation, capability, or similar capacity to interpret or operationalize information
Operational complexity	When the ability to accomplish a task is incumbered by complicated or seemingly unnecessary steps
Organizational readiness	When actors within the organization lack the capabilities or resources to accomplish tasks

Logic Model

The logic model provides a visual representation of the main circumstances and conditions that influence the absorptive organizational design decisions made by the hospital administration of the case organization. Furthermore, a logic model " represents a program archetypal, usually in the form of a diagram" (Funnell & Rogers, 2011, p. 34). Lastly, the logic model analysis technique operationalizes a complex chain of events over an extended time to illustrate how a complex activity took place (Funnell & Rogers, 2011). **Figure 6** below presents the key elements of the BDA process at the case organization derived from the data analysis. This model will help contextualize the major and minor themes discussed in the study results section to follow.

Figure 6

Logic Model BDA Process



Evidence of Trustworthiness

Trustworthiness provides a framework for others to evaluate the value of qualitative inquiry (Stahl & King, 2020). Credibility, transferability, dependability, and confirmability are the four ways to assess evidence of trustworthiness. The following paragraphs outline objective evidence of trustworthiness.

Credibility

Credibility, in qualitative inquiry, is the extent to which a concept or phenomenon is measured (Heale & Twycross, 2015). Evidence of credibility was observed in several but not all the strategies employed in this study. First, RDT, the theoretical framework of this study, relates to the control of external resources and capabilities. Several interview participants referred to developing capabilities and resource gaps when describing their experience with BDA. Second, interview participants from multiple embedded units described similar experiences regarding implementing BDA. Thirdly, most participants volunteered to continue the interview beyond the planned 30-minute duration. The interview of one participant lasted approximately 90 minutes, suggesting that maintaining confidentiality promoted rich and detailed responses. Lastly, reflexive journaling prompted me to modify the interview guide to improve the flow of subsequent interviews. Although the credibility strategy was not altered, reaching thematic saturation after seven interviews suggests credibility was achieved.

Transferability

Transferability refers to the extent the results of a study can be applied to similar phenomena in different contexts (Stahl & King, 2020). Although I did not modify the transferability approach, it is worth noting that augmented member checks produced little data. Above in the research setting section, I provided a detailed context of the case organization. All interview participants held senior-level positions with expert knowledge of BDA at the case organization. Furthermore, participants represented a homogenous sample of the organization.

Dependability

Dependability refers to the reliability of study findings (Yin, 2018). To promote dependability, I utilized verbatim transcripts of interviews, reflexive auditing, hypothesis coding, and triangulation. Verbatim transcripts were very helpful in comparing coding to questions across participants examples are outlined in

Table **7**. Reflexive auditing highlighted my bias toward participants with technical and industry backgrounds, in which I was able to build a rapport very quickly versus clinical participants. My bias stems from my technical experience in IT and other industries. Based on systematic hypothesis coding, I also observed common themes and codes across participants. For example, several participants referred to "external capabilities" when discussing external partnerships. Finally, during triangulation with secondary data, the details correlated with the input from participants. For example, one participant discussed the need to "shorten the time from research to clinical practice," and a secondary data source mentioned "clinical and translational research."

Confirmability

Confirmability refers to neutrality in the study findings (Yin, 2018). I did not change the confirmability strategies and I observed evidence of confirmability in the reflexive auditing process and hypothesis coding process. As with the dependability above, the reflexive auditing process helped me recognize my bias toward participants with technical and industry backgrounds. As such, I adjusted my interview technique to remain more neutral. Also, hypothesis coding and content analysis.

Study Results

The research question for this study was to identify the circumstances and conditions that influence hospital administration absorptive organizational design choices to mitigate information asymmetry from a BDA implementation. Therefore, the open-ended interview guide contains three domains of inquiry. The first domain focuses on the drivers and external influences behind BDA adoption. In contrast, the second domain addresses the organizational changes (i.e., management, structure, BOD, and external partnerships) to accommodate BDA. Finally, the third domain includes a discussion of the capabilities and resources needed for BDA initiatives.

Pre-Code Definitions Phase 2

Resources and capabilities are core factors to consider when designing organizations (Ashraf, 2017). The predominant themes that emerged during phase 2 coding were capability acquisition, dispersed capability, asymmetry between clinical and technical teams, intellectual capacity, and organizational separation. Table 10 presents a summary of participant phrases associated with the corresponding code.

Table 10

Results of Phase 2 Coding

Pre-code	Phrase
Capability acquisition	"as they bring in new people with new skills sets" "most acquired from outside with new skills" "exploring new external capabilities" "I think health systems like ours have had to add different skill sets"
Physician leadership	"many of our analytics leaders have physician backgrounds"
Boundary spanning	"we've learned that virtual teams charged with solving a specific problem works well for us"
Risk based contract	"population health contracts are a new effort. We are learning"
Slow vendor development process	"try not to rely on vendors. The time to respond is costly"
Resource buffering	"centralized data warehouse"
Organizational separation	"we ensure a clear structure with clear lines of reporting"
Strategic interdependence	"our teams are made up of data analytics, business, and clinical folks"
Intellectual capacity	"internally we have people in technical roles with math backgrounds that could transition to data scientist roles"
Capability follows demand	"that new position at executive level first began as an embedded role" "it was gradual as more data became available"
Asymmetry between clinical and technical	"there's 8 departments with asymmetry on both sides" "asymmetry on the technical side as well as the clinical side" " We don't have an information asymmetry issue it's a big data analytics lack of understanding issue"
Dispersed capability	"that group sit outside our IT department and that's made a big difference"

Hypothetical Activity Coding Phase 3

Participants alluded to various activities resulting from the implementation of BDA into their operations. The main activity themes were new role assignment, capability acquisition, as well as evolving roles and demands. There was one code instance regarding BOD and data analytics, but the activity did not constitute a change instead just an acknowledgment that data analytics helped inform BOD decisions. The merger activity code was not assigned during this phase. Table 11 presents a summary of hypothetical activity codes with participant phrases associated with those codes.

Table 11

Hypothetical Activity Code Phase 3

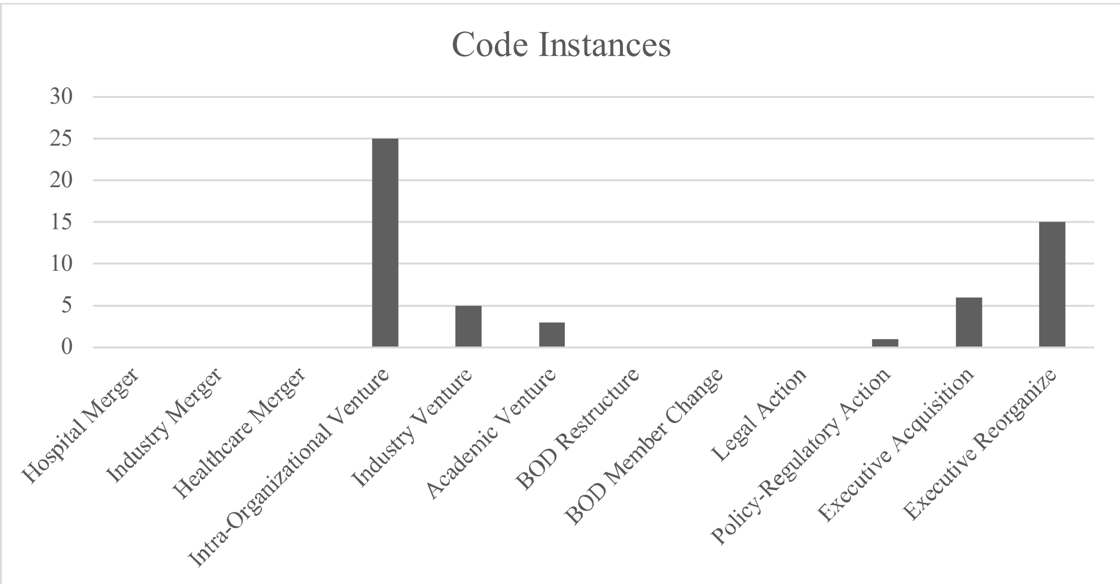
Hypothetical activity code Phase 3	Phrase
New role assignment	"Most skills are acquired from outside the organization…and definitely bringing in different skill sets" "it's a trust factor there and trusting what was coming out and so external sources are beginning to drive those clinical standardization projects" " over time you added in technology folks to serve and help to automate the on-boarding of that data and so now point resources were added to start gathering at first people try to accommodate to get the data themselves"
Evolving role	"roles and responsibilities are constantly changing and realigning, especially at the leadership level"
New governance	"we are always trying to improve the quality of our data"
Net new technology resource	"First began by then hiring and bringing in documentation nurses data extraction nurses"
Centralized resource	"our data warehouse has been centralized for years" "dedicated team to manage the warehouse"
Capability development	"the decision to move toward developing new capabilities and big data was motivated by a few factors one which is tied to this value-based contract change for me many years we've been aware of the accelerating of the cost of healthcare and there's been a real interest among payers to slow that down that's applied pressure to healthcare systems"
Partner resource	"we are constantly relying on our vended IT partners"
Merged resource	"no mergers that I am aware"
BOD adjustment	"we have a subcommittee focused on data analytics"
Executive leadership acquisition	"the head of our innovation came from outside the hospital"
Organizational realignment	"we are constantly changing the structure of the organization"
New functional group	"we now have dedicated technology analytics teams"
Evolving demands	"Adoption of big data analytics was more a natural evolution of just business demand"

Theoretical Coding Phase 4

Theoretical coding in phase 4 displayed in Figure 7 revealed intra-organizational ventures was the predominant theme (25 out of 55), followed by executive acquisition and executive reorganize (combined, 21 out of 55). External organizational ventures (8 of 55) represented by industry and the academic venture was also present to a lesser extent. Lastly, Policy/Regulatory, including legal actions, predicted by RDT was nominally present (1 out of 55). The RDT merger activity was not present, represented by the codes hospital, industry, and healthcare merger. Furthermore, the RDT activity of BOD adjustments represented by the codes BOD restructure and BOD member change were also absent.

Figure 7

Theoretical Coding Phase 4

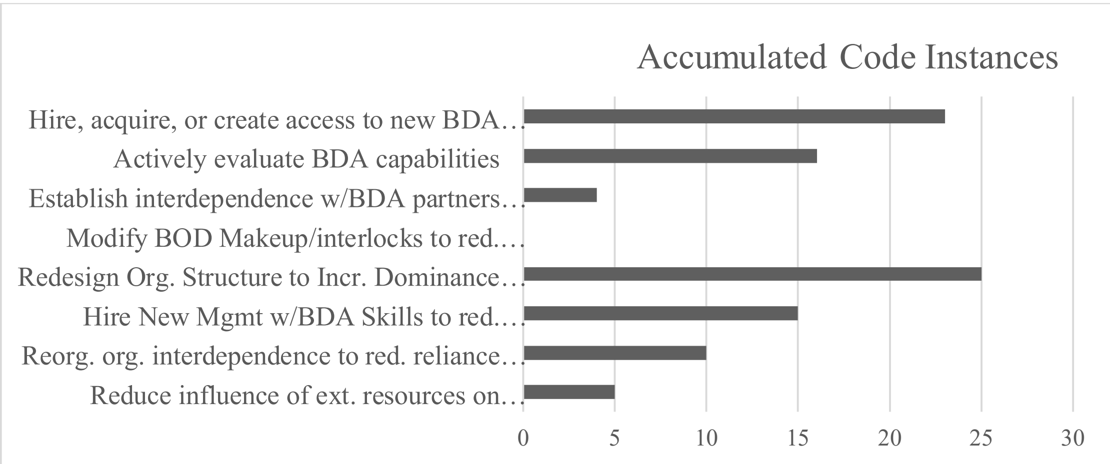


Interview Questions Phase 5

In phase 5 of the data analysis the interview questions aligned with predicted hypothetical actions and coupled with multiple codes as shown in Figure 8. The figure shows that the themes of hiring new BDA experts, redesign organization, and hire new management are dominant themes. While actively evaluate BDA capabilities and reduce reliance on external resources are also important.

Figure 8

Interview Questions Phase 5 Results

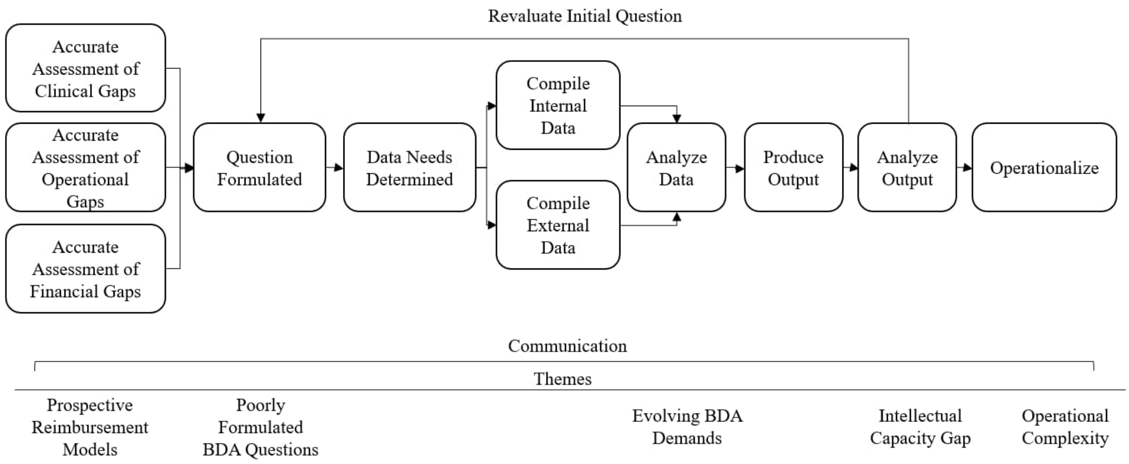


Major and Minor Codes Phase 6

The major theme was found to be communication encompassing the minor themes of prospective reimbursement models, poorly formulated BDA questions, evolving BDA demands, intellectual capacity gap, and operational complexity. **Figure 9** illustrates how the major and minor themes align with the logic model first presented in the data analysis section.

Figure 9

Major and Minor Codes Aligned with Logic Model



Summary

This qualitative single case study aimed to explore the circumstances and conditions that influence hospital administration organizational design absorptive choices to reduce information asymmetry caused by BDA. The results in this Chapter 4 described the research setting data collection, data analysis, evidence of trustworthiness, and study results. Primary data were gathered from 12 participants via open-ended interviews after IRB approval and informed consent. I also compiled secondary data from publicly available internet information and a marketing database.

Data analysis revealed a major theme of communication that encompasses the five minor themes of prospective reimbursement models, poorly formulated BDA questions, evolving BDA demands, intellectual capacity gap, and operational complexity. I conducted the data analysis over six data readings using hypothesis coding and theoretical coding techniques. I conducted a further analysis using a logic model approach to map process elements against RDT theoretically predicted actions. Chapter 5 contains a discussion of the themes, conclusions, limitations, implications, and recommendations.

Chapter 5: Discussion, Conclusions, and Recommendations

This qualitative single case study aimed to explore the circumstances and conditions that influence hospital administration organizational design decisions toward reducing information asymmetry from BDA initiatives. More specifically, to understand the influences over absorptive organizational design choices such as corporate mergers, executive administration changes, board of director adjustments, or organization structural changes. The study consisted of expert interviews with 12 participants from a single U.S. hospital triangulated with secondary data from financial reports, press releases, and a marketing database. The research problem was viewed through the lens of RDT, which predicts hospital administration will take specific actions to reduce reliance on external resources to bolster its business model.

While the correlation between BDA organizational, firm, and financial performance is well supported, extant research has paid little attention to exploring the organizational design issues resulting from BDA. The U.S. health system is one of the poorest financially performing in the world. As a result, hospital administrations are under pressure to reduce costs and often turn to BDA initiatives. The five key themes that emerged from this study are

- prospective reimbursement models
- poorly formulated BDA questions
- intellectual capacity gap
- operational complexity
- evolving BDA clinical, financial, and operational demands

Interpretation of Findings

This study is unique in that I explored, through a lens of RDT, the circumstances and conditions that influence absorptive choices of hospital administration undertaking BDA implementations. As described earlier, RDT predicts that hospital administration will engage in activities to reduce its reliance on external resources. Critical resources related to BDA are typically outside the direct control of hospital administration. For instance, population health data, BDA analytics, and visualization tools, specialized analytics capabilities, and management expertise. According to RDT, hospital administration may take absorptive actions such as hiring new executive leadership, adjustments to BOD makeup, intra-organizational restructuring, new partnerships, or engaging in joint ventures to secure access to those resources.

A common refrain from participants of this study is that the implementation of BDA into a hospital operational paradigm is not the primary influence over organizational design decisions. Instead, BDA is one of many elements to consider when deciding to undertake an absorptive design decision, such as acquiring new capabilities or merging with another organization to bolster existing capabilities. Participants acknowledged the many challenges of BDA. Especially its implementation in healthcare is the merger of two disparate and complex systems. Nevertheless, fundamentally, organizational design decisions must consider many factors, including how to mitigate the level of information asymmetry.

Overall, the findings of this study affirm that RDT is relevant to mitigating information asymmetry in BDA hospital deployment environments. Specifically for the prescribed activities of executive changes and intra-organizational ventures, there was no evidence that BOD, M&A, or regulatory activities influenced organizational design decisions.

Communication was the overarching major theme derived from this study, whereas minor themes are prospective reimbursement models, poorly formulated BDA questions, evolving BDA demands, intellectual capacity gap, and operational complexity. These information asymmetric themes represent the pre-requisite conditions and circumstances that influence absorptive organizational design decisions.

Before discussing the central themes of this study, a brief review of the three underlying assumptions is prudent. First, the hospital administration desires to increase its reliance on BDA to improve its data-driven decision-making capabilities. Second, hospital administration recognizes the power (i.e., information asymmetry) BDA experts hold given their superior, actionable information over consumer groups. Thirdly, hospital administration will take organizational design actions to reduce the level of information asymmetry from BDA. The first two assumptions provide context, but the third presents the theoretical framework for which this study is viewed. The following sections present a discussion of the main themes derived from this study.

Prospective Reimbursement Models

The most frequent terms used by participants when discussing the drivers behind adopting BDA was patient population health, value-based care, and health economics. Traditional reimbursement models in the U.S. healthcare system are retrospective. BDA is a critical element of prospective reimbursement models that shift payments to upfront monthly and are measured by population health outcomes (Kokshagina, 2021). Confirming the underlying premise of this study, several participants described how prospective reimbursement models revealed gaps in capabilities and recognized a high level of information asymmetry between the clinical and operational staff throughout the organization. To mitigate the information asymmetry, hospital administration implemented a “hub and spoke” organizational governance design. This design mirrors the findings of Levy et al. (2022), in which a healthcare system is taking steps toward a self-service BDA strategy.

Hospital administration explored augmenting existing capabilities with highly specialized capabilities as the information asymmetry decreased. Augmentation via university partnerships and new vendor tool acquisitions. The above suggests an interdependence between external resources and internal resources.

Poorly Formulated BDA Questions

The process of implementing BDA solutions is very complicated, especially in healthcare. Furthermore, there is a high level of business expectation around the concept of BDA; however, the resulting information is only as good as the questions asked. Furthermore, healthcare personnel are not typically versed in the language of business. Often, users are not familiar with the data available to them, nor are they capable of asking the relevant questions given the available data. Several participants mentioned the barrier of poorly formulated questions from the users or consumers of BDA information. One participant said that users of the case organization should take a more scientific approach to question formulation. A scientific approach presumes BDA consumers are familiar with the scientific method in a properly formed problem statement coupled with a properly formed question, followed by the appropriate analytic tools to address the issue.

The above deficit was evidenced as two participants mentioned instances where analytic nursing staff with a general knowledge of data analytics were hired to interface with core healthcare personnel. The same participants mentioned that similar capabilities were available from their vendor partners, but those interactions were burdensome because those resources lacked familiarity with internal clinical operations. Following this logic, the absorptive hiring strategy could be avoided if vendor partners were familiar with the internal operations of their client hospitals. According to Ferri and Griffiths (2021), healthcare practices are context-specific, but evidence-based medicine must be adopted to aid in disseminating guidelines and standards to provide patients with the best possible outcomes. These findings suggest that hospital administration focused on strategies to standardize operations may be better positioned to utilize external resources.

Intellectual Capital Gap

Like the above phenomenon, information asymmetry manifests as a gap in the intellectual capital of BDA consumers. According to most participants, the gap is two-fold. First, BDA consumers cannot understand the information produced by BDA experts, typically numerical or statistical. Second, BDA consumers are unable to transform the information into operational action. To address this gap, hospital administration assigned a net new role of chief data and analytics officer (CDAO) charged with overseeing enterprise analytics and data governance. In addition, both centralized and decentralized departmental analytics resources were allocated.

According to the CDAO, the centralized analytics resource has more BDA expertise than the departmental resource. In contrast, the departmental resource has more business and operational insight with only a general knowledge of BDA. To improve BDA implementation and communication across groups, the CDAO said they would place a BDA expert with operational experience from the central group within the department. The CDAO described these roles as hybrid and the approach as a "hub and spoke" or boundary spanning model. Often these resources were net-new from outside the organization. This strategy aligns with the findings of Levy et al. (2022), revealing that boundary spanning is a best practice for managing data governance. Also, Schiavone et al. (2022) found that creating visual dashboard tools for monitoring operations and communicating was a strategy to increase the intellectual capital of BDA users and consumers. The above suggests that hospital administration should invest in visualization tools and reduce the organizational separation between hybrid resources to improve the intellectual capital across the healthcare enterprise.

Operational Complexity

The healthcare ecosystem is a complex mix of providers, vendors, IT, medical technology, and logistics (Velthoven et al., 2019). The low overall performance in the healthcare space is a major contributing factor to the cost of healthcare in the United States (Golden, 2006). Several participants mentioned that operationalizing BDA solutions was a challenge, particularly given the self-regulating tendencies of incumbent actors within the healthcare value stream. To address the challenge, the hospital administration of the case organization engaged a university industrial engineering resource on an interim basis. According to participants, the objective was to evaluate workflows, interfaces, and care pathways to identify opportunities for improvement. Long term, according to participants, the resource would become a net new role within the case organization.

The absorption of an industrial engineering resource suggests that the self-regulating tendencies of incumbent actors have a moderating effect on operational transformations. Along this line of reasoning, Siachou et al. (2021) found that organizational absorptive capacity and strategic interdependence among actors are factors in how apt an organization is to accept change. These findings suggest that hospital administration employing a boundary-spanning design strategy among incumbent actors would limit their moderating effect on performance. Additionally, multidisciplinary teams have positively impacted patient outcomes (Epstein, 2014). Although healthcare is operationally complex, the use of boundary-spanning organizational design strategies and multidisciplinary teams may limit the use of external resources.

Evolving BDA Demands

Most participants revealed that the demands of BDA solutions across the case organization were in constant flux. Some participants alluded to the multiple changes in organizational design as an indication that needs were evolving. Other participants discussed the addition of executive leadership with varying technological backgrounds. Yet others described the emergence of departmental data analytics tools and databases.

Strategically, the hospital administration of the case organization endeavored to consolidate resources and implement data governance across the enterprise to organize BDA demands.

Additionally, virtual teams comprised BDA experts, users, vendors, and hospital administration to capture BDA demands. One participant described the central issue as the same question being asked by different departmental users disproportionately consuming limited BDA resources. Then hospital administration hired demand managers with project management expertise to manage the work of the virtual teams. Evolving BDA demands had a cascading resource-absorbing impact on the organization.

The challenge is how to exploit existing BDA innovations for different functional areas of the organization. Adding new roles to manage evolving and duplicative BDA demands suggests a reluctance to accept innovation among BDA users. According to Aceto et al. (2018), communication technologies play a primary role in promoting innovation. Warty et al. (2021) identified six barriers to technology adoption in healthcare, but the most relevant in this context is the lack of clinical evidence and user uncertainty. These findings suggest that educating BDA users about the underlying technology would promote the adoption of innovations. Furthermore, showing BDA users the benefits of the prescribed solution would improve adoption. Along this line of reasoning, hospital administration should invest in communication technologies highlighting BDA solutions successes and develop mechanisms to educate users about the underlying technology.

Limitations of the Study

In Chapter 1, there were four limitations identified in this study: (a) the potential for results to be context-dependent, (b) access to interview participants, (c) access to organizational documentation, and (d) IRB policies restricting support for external research initiatives.

The results of this study are context-dependent for two reasons. First, case organization leadership initiated an enterprise-wide prospective reimbursement model approach which, as suggested by several interview participants, affects BDA initiatives (e.g., types of data sources, types of analytic skills needed, and user interpretive capabilities). The specific reimbursement model was not initially contemplated as a factor in this study and may restrict the transferability of results. Second, the participants described multiple BDA implementations, resulting in varying success. Personnel, practices, and strategies from prior initiatives were carried over to the current BDA implementation. The carryover is a limitation as it is impossible to distinguish clearly between the circumstances and conditions attributed to prior deployments.

Access to interview participants was not a limitation. Participants were homogeneous from the case organization, including IT personnel, healthcare administration, BDA users, and experts. As mentioned in Chapter 2, the stream of BDA and information asymmetry literature overly relies on sampling IT personnel. Only two of the interview participants revealed during the interview that they either directly or indirectly hierarchically report through the IT organization.

Lastly, IRB policies and access to organizational documentation were identified as study limitations. IRB policies were not a limitation; however, access to organizational documentation was restricted by the organization. As a result, I had to rely on publicly available secondary data sources.

Recommendations

The following sections include recommendations for future research on reducing the reliance on external resources in highly asymmetric healthcare environments. First, the results of this single-site study suggest executive succession and intra-organizational ventures are the predominant activities undertaken by hospital administration to reduce reliance on external resources. A subsequent multi-site study with the same research design would further refine the RDT activities and test transferability.

High information asymmetry is a design strategy in federated digital data architectures (FDDA) which are growing in popularity as a means to control hospital-owned data yet maintain interoperability with disparate groups (Kumar et al., 2018). FDDA implementation is typically a precursor to the business strategy of monetizing digital data assets (De Luca et al., 2020). Internally, from an organizational design perspective, FDDA purposely aggravates the level of information asymmetry to enforce digital data control. A qualitative study through the resource-based view lens investigates how buffering organizational design strategies are employed to enforce asymmetry in FDDA environments. A buffering scheme cordons core operations from external influences to manage resources. As mentioned in Chapter 1, the resource-based view is an extension of RDT, focusing on the use of available resources to gain a competitive advantage.

The additional research recommendations below focus on the two RDT activities of executive succession and intra-organizational structure, as well as prospective reimbursement models. Prospective reimbursement was a common theme from participants of this study, suggesting the model impacts organizational design strategies and resource dependence in healthcare.

Prospective Healthcare Reimbursement Models

Prospective reimbursement in healthcare is cast as population health and stems from changes in the U.S. regulatory schema designed to enhance the health of a particular population. The U.S. Federal Government will provide prospective reimbursements to hospitals that agree to take actions to improve the well-being of a specific population (Kruse et al., 2018). BDA is a common tool employed by hospital administration to identify the optimal allocation of limited resources (Strang & Sun, 2020).

Investigating how the use of prospective reimbursement model contracts impacts organizational design decisions through the lens of RDT would be an excellent future qualitative study (Shrank et al., 2019). Similarly, a future qualitative study investigating how resources and capabilities are allocated in hospitals with prospective reimbursement models. Lastly, a qualitative study investigating the use of boundary-spanning strategies in prospective reimbursement model environments. A focus on boundary spanning is interesting because the method involves creating interdependencies between internal and external resources to meet population health goals set by the prospective reimbursement contract with the payee.

Executive Succession

As discussed in Chapter 2, the roles of chief data officer and chief digital information officer are emerging in healthcare, particularly with BDA-oriented top leadership. Current research focuses on their responsibilities and their impact on operational and financial performance. According to the literature, data officers focus on leveraging digital data (e.g., analytics, data access, data governance) across the enterprise to meet organizational goals. An interesting qualitative study would investigate the resource design strategies of chief data officers charged with BDA implementations.

The chief digital information officer is distinguished from data officers as they are typically charged with the broader operational scope in a healthcare paradigm. The scope may include network infrastructure, business systems, and analytical systems. A similar qualitative study investigating the strategies of controlling reliance on external resources would help build on the findings of this study.

Intraorganizational Structure

The study findings revealed communication was an overarching theme. The participants described the formation of various multidisciplinary teams to address BDA business problems. A future qualitative study investigating multidisciplinary team formation strategies through the lens of diffusion of information theory would build on this study.

Another theme of this study was operational complexity, particularly the interactions with external vendors. Boundary spanning is the strategy of establishing relationships with external actors to meet business goals (Joshi et al., 2009). A future qualitative study investigating configurations to optimize boundary-spanning relationships with vendors in a healthcare BDA context would build on this study.

Implications

The results of this research study provide insight into hospital administration's absorptive choices designed to mitigate high information asymmetry from BDA. This study may lead to positive social change by providing research on how hospital administration can more effectively allocate resources and improve communication in highly asymmetric healthcare environments. Communication was the overarching theme derived from this study. The following paragraphs describe the impact on positive social change, methodological implications, theoretical implications, and practice recommendations.

Positive Social Change

This study may lead to positive social change for individual BDA users and experts by providing qualitative research into communication strategies in highly asymmetric environments. For instance, the results of this study suggest that the capability of creating well-formed BDA questions may increase an individual's understanding (i.e., intellectual BDA capital) of the applicability of BDA in the hospital paradigm. Furthermore, improved intellectual BDA capital may lead to more innovative solutions from individuals.

The results of this study may lead to positive social change for multidisciplinary groups by improving communications among individual actors. The themes derived from this study were formulating good BDA questions, evolving BDA demands, intellectual capacity gap, and operational complexity. Improving group communication capabilities along these lines may enhance multidisciplinary group performance by lowering information asymmetry, ultimately resulting in better healthcare solutions from BDA.

The results of this study may lead to positive social change for the healthcare organization by optimizing the use of existing resources with increased efficiencies. In addition, the impact on society may be improved patient clinical outcomes. One study participant said the goal of BDA in healthcare is to "decrease the 17-year gap between research and clinical practice".

Methodological Implications

The methodological design was a strength of this study for two reasons. First, prior studies performed through the lens of RDT focused on a specific predicted activity (e.g., BOD changes or M&A). Qualitative methodology was appropriate as there was no prior research in this domain. Furthermore, since this is an early-stage study, the design focused on all RDT-predicted activities to determine the theoretical relevance of healthcare BDA implementations. Second, the population of this study was more appropriate for investigating resource allocation by including users or consumers of BDA rather than only IT personnel, as in many other studies.

Overall, the research design was sound; only the interview guide and coding process was modified during the study. The Open-Ended Interview Guide was refined after the first interview to improve the logic of the interviews as well as to improve the focus on resource allocation. Also, some specific demographic questions (e.g., gender, age, and ethnicity) were removed for lack of relevance to the subject material. The pre-coding process was revised for a more step-wise transition from participant input to specific codes to general RDT-relevant coding.

Theoretical Implications

This study makes several contributions to RDT organizational design research. First, this study tested RDT in a highly information-asymmetric healthcare context. RDT predicts that hospital administration will take action to reduce reliance on external resources. The results of this study affirm the relevance of executive changes and intra-organizational ventures in highly asymmetric healthcare environments. No evidence was found to suggest the RDT activities of changes in the BOD, M&A or political actions are relevant in highly asymmetric healthcare environments. These findings add to the existing organizational design strategies for BDA implementations.

Recommendations for Practice

I have developed several recommendations on communication, resource allocation, and organizational design in a highly information-asymmetric healthcare environments. According to the literature, many BDA initiatives are episodic and tend to evolve. These characteristics were present at the case organization.

First, this study demonstrates that communication between BDA information consumers and producers is paramount. Consumers are typically healthcare professionals that use complex medical terminology, while BDA experts employ technical language.

As Y. Wang et al. (2019) observed, hospital administration should place analytical personnel with a broad combination of technical, soft skills, and multidisciplinary knowledge domains in strategic positions to help bridge the divide between consumers and producers of BDA-derived information.

Second, organizational structures should be flexible, as resource allocation should be transitory. Resources may need to be reallocated as organizational capabilities mature. Hospital administration should continually survey consumers and producers of BDA information to determine what practices hinder the organization and adjust accordingly. In the short term, hospital administration should boundary span by establishing relationships with technical universities and work collaboratively to fill gaps. Those capabilities may be bridged in the longer term by creating university programs with internship dependencies as the organizational BDA capabilities evolve and mature.

Lastly, organizational design, as suggested above, should be flexible. Hospital administration should consider a modified "hub and spoke" design. They are modified, meaning placing higher analytical and technical skilled personnel on the *spoke*, organizationally closer to consumers. As the communication skills grow and the operational knowledge improves of organizational actors, hospital administration should migrate resources centrally toward the *hub*. Then, repeat, as necessary, the modified strategy elsewhere within the organization.

Conclusions

Extant research has paid little attention to exploring the organizational design issues resulting from information asymmetry caused by BDA. In particular, costly

organizational absorptive choices include acquisitions, mergers, reorganization, executive changes, board of director adjustments, or new hires. Through the lens of Pfeffer and Salancik's RDT, this study explored the circumstances and conditions that influence hospital administration's costly absorptive organizational design choices. Communication was the major theme encompassing minor themes of poorly formed BDA questions, prospective reimbursement models, evolving BDA demands, intellectual capacity gap, and operational complexity are the conditions and circumstances influencing design decisions. Findings suggest executive changes and intra-organizational activities moderate information asymmetry. The theoretical implication of this study is that it affirms the relevance of RDT within a healthcare ecosystem. The practical implications emphasize communication, multidisciplinary groups, and flexible "hub and spoke" organizational design strategies. Lastly, the positive social change implications from this study may increase BDA adoption in healthcare.

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Appendix A: Open-Ended Interview Guide

Opening Statement

Thank you again for taking time out of your schedule to participate in this research. The aim of this study is to understand the conditions and circumstances that influence organizational design choices for the implementation of big data analytics. You have been selected for this study based on your experience, knowledge, and expertise on this topic. This interview should take no more than thirty minutes. Is that, OK?

As stated in the invitation and informed consent, your privacy and confidentiality including your interview responses will be maintained throughout this research. Any information used from your responses in data analysis will remain anonymous. As a reminder, our session will be recorded to help me in the notetaking and transcription process. Do you have any questions for me before we get started?

If you are OK to continue, I will start the recording now and begin with our first question.

Interview Questions

1. Demographic data
    a. How long have you been in your current role?
    b. What is your current job title?
    c. What is your highest level of education?
2. Tell me about how the decision to adopt big data analytics at your hospital came about.

a. Probe: Tell me about the drivers behind the decision to adopt big data analytics.

b. Probe: Tell me about any external influences on the decision to adopt (if not directly answered)

3. How has the organization changed to accommodate big data analytics initiatives?

   a. Probe: Tell me about any changes in management

   b. Probe: Tell me about any structural changes or intra-organizational realignments (if not directly answered)

   c. Probe: Tell me about any changes in the board of directors (if not directly answered)

   d. Probe: Tell me about in external partnerships (if not directly answered)

4. Tell me about the capabilities needed for big data analytics initiatives.

a. Probe: How did management address any gap in capabilities? (if not directly answered)

5. Do you have any feedback on topics that we did not cover but should have covered?

6. Do you have any questions for me?

Closing the Interview

Provide the participant an opportunity to provide additional relevant information by asking the question: “Is there anything you would like to share that you think is relevant but we have not discussed?”

Augmented Member Checking

Provide the participant with the following information to ensure they understand the follow-up and next steps of the study. “I will email you a summary of the overall themes of our discussion today. This will give you an opportunity to clarify or amend anything I have captured today. I ask that you return any feedback within 5 days. I may follow up a second time to gather information on new topics that arise from your input. I ask that you again provide any feedback within 5 days. Is that OK?”

Appendix B: Pre-Coding Categories based on Theoretical Framework

Theme	Code Description	Code	Code Definition
Mergers & acquisitions	Hospital Merger	MA1	Merger between hospitals to leverage Expertise in AI/Big Data to reduce uncertainty
	Industry Merger	MA2	Hospital acquires industry expertise in AI/Big Data via merger to reduce uncertainty
	Health Care Merger	MA3	Health care manufacturer to merge with hospital or industry to acquire expertise
Joint venture	Intra-Organization	JV1	Reorganizing the hospital organization to leverage AI/Big Data expertise
	Industry	JV2	Venture between a hospital and industry or health care company to acquire AI/Big data expertise
	Academic	JV3	Venture between a hospital and university or college to expand or buttress resources or capabilities
Board of directors (BOD)	BOD restructure	BOD1	Change the structure (expand or contract) of the BOD to acquire resources or expertise
	BOD member change	BOD2	Bring in expertise to the BOD
Political actions	Law	PA1	Hospital lobby state, federal, or local government to enact laws to reduce uncertainty with AI/Big data
	Policy/Regulation	PA2	Hospital lobby regulatory body to enact regulations to reduce uncertainty
Executive succession	Executive Change	ES1	Change in executive leadership to acquire expertise or realign responsibilities

Note. The themes are derived from the five dimensions of RDT (Salancik et al., 1978).

Appendix C: De-Identified Data-Use Agreement

De-Identified Data Use Agreement

Background

A data use agreement allows a researcher to share a limited data set with a colleague or another person or entity not associated with the study or the researcher's institution.

An Institutional Review Board (IRB) must be notified if a researcher or institution plans to share a limited data set with a recipient (person or entity) not named in the original IRB application. That recipient must sign a data use agreement before the limited data set is shared. A data use agreement is not required if the recipient is part of the trial and is included in the IRB Authorization or waiver of Authorization approval for the trial.

Of note:

(a) Limited data sets are not subject to the HIPAA Accounting for Disclosures provisions.

(b) Under 2013 revisions to HIPAA, unauthorized uses or disclosures of a limited data set may constitute a 'breach' for breach notification rule purposes.

If you have questions about the information above or the need for a data use agreement, please consult Notre Dame Research Compliance or the University's General Counsel.

What is a Limited Data Set?

A "limited data set" is defined as health information that excludes certain direct identifiers (listed below) but that may include city; state; zip code; elements of date; and other numbers, characteristics, or codes not listed as direct identifiers (below). The Privacy Rule's limited data set provisions requiring the removal of direct identifiers apply both to information about the individual and to information about the individual's relatives, employers, or household members.

The following identifiers **must** be removed to qualify as a limited data set:

1. Names
2. Postal address information (other than town or city, state, and zip code)
3. Telephone numbers
4. Fax numbers
5. Electronic mail addresses
6. Social security numbers
7. Medical record numbers
8. Health plan beneficiary numbers
9. Account numbers
10. Certificate/license numbers
11. Vehicle identifiers and serial numbers (including license plate numbers)
12. Device identifiers and serial numbers
13. Web universal resource locators (URLs)
14. Internet protocol (IP) address numbers

15. Biometric identifiers, including fingerprints and voiceprints
16. Full-face photographic images and any comparable images

What is a Data Use Agreement?

A data use agreement is the means by which covered entities obtain satisfactory assurances that the recipient of the limited data set will use or disclose the PHI in the data set only for specified purposes. Even if the person requesting a limited data set from a covered entity is an employee or otherwise a member of the covered entity's workforce, a written data use agreement meeting the Privacy Rule's requirements must be in place between the covered entity and the limited data set recipient.

DATA USE AGREEMENT FOR LIMITED DATA SETS

This Data Use Agreement ("Agreement"), effective as of ________, 20__ ("Effective Date"), is entered into by and between __________________ ("Recipient") and ________ ____________ ("Covered Entity"). The purpose of this Agreement is to provide Recipient with access to a Limited Data Set ("LDS") for use in the following titled research project: ________________________________ (Project Name) under the direct supervision of ________________________________ (Principal Investigator) in accord with the HIPAA Regulations.

Definitions. Unless otherwise specified in this Agreement, all capitalized terms used in this Agreement not otherwise defined have the meaning established for purposes of the "HIPAA Regulations" codified at Title 45 parts 160 through 164 of the United States Code of Federal Regulations, as amended from time to time.

Preparation of the LDS. Covered Entity shall prepare and furnish to Recipient a LDS in accord with the HIPAA Regulations. **NOTICE: This agreement is valid only if the Data do not include any of the following "Prohibited Identifiers": Names; postal address information other than town, cities, states and zip codes; telephone and fax numbers; email addresses, URLs and IP addresses; social security numbers; certificate and license numbers; vehicle identification numbers; device identifiers and serial numbers; biometric identifiers (such as voice and fingerprints); and full face photographs or comparable images.**

Minimum Necessary Data Fields in the LDS. In preparing the LDS, Covered Entity or its Business Associate shall include the data fields specified by the parties from time to time, which are the minimum necessary to accomplish the purposes set forth in Section 5 of this Agreement.

Responsibilities of Recipient.

Recipient agrees to:

Use or disclose the LDS only as permitted by this Agreement or as required by law;

Use appropriate safeguards to prevent use or disclosure of the LDS other than as permitted by this Agreement or required by law;

Report to Covered Entity any use or disclosure of the LDS of which it becomes aware that is not permitted by this Agreement or required by law, including the presence of prohibited identifiers in the LDS;

Require any of its subcontractors or agents that receive or have access to the LDS to agree to the same restrictions and conditions on the use and/or disclosure of the LDS that apply to Recipient under this Agreement; and

Not use the information in the LDS, alone or in combination to identify or contact the individuals who are data subjects.

Permitted Uses and Disclosures of the LDS. Recipient may use and/or disclose the LDS only for the Research described in this Agreement or as required by law.

Term and Termination.

Term. The term of this Agreement shall commence as of the Effective Date and terminate 5 years from Effective Date. Should the Recipient desire to keep the LDS for a longer period, a justification in writing should be made to the Covered Entity.

Termination by Recipient. Recipient may terminate this agreement at any time by notifying the Covered Entity and returning or destroying the LDS.

Termination by Covered Entity. Covered Entity may terminate this agreement at any time by providing thirty (30) days prior written notice to Recipient.

For Breach. Covered Entity shall provide written notice to Recipient within ten (10) days of any determination that Recipient has breached a material term of this Agreement. Covered Entity shall afford Recipient an opportunity to cure said alleged material breach upon mutually agreeable terms. Failure to agree on mutually agreeable terms for cure within thirty (30) days shall be grounds for the immediate termination of this Agreement by Covered Entity.

Effect of Termination. Sections 1, 4, 5, 6(e) and 7 of this Agreement shall survive any termination of this Agreement under subsections c or d.

Miscellaneous.

Change in Law. The parties agree to negotiate in good faith to amend this Agreement to comport with changes in federal law that materially alter either or both parties' obligations under this Agreement. Provided however, that if the parties are unable to agree to mutually acceptable amendment(s) by the compliance date of the change in applicable law or regulations, either Party may terminate this Agreement as provided in section 6.

Construction of Terms. The terms of this Agreement shall be construed to give effect to applicable federal interpretative guidance regarding the HIPAA Regulations.

No Third Party Beneficiaries. Nothing in this Agreement shall confer upon any person other than the parties and their respective successors or assigns, any rights, remedies, obligations, or liabilities whatsoever.

Counterparts. This Agreement may be executed in one or more counterparts, each of which shall be deemed an original, but all of which together shall constitute one and the same instrument.

IN WITNESS WHEREOF, each of the undersigned has caused this Agreement to be duly executed in its name and on its behalf.