BEDELEY, RUDOLPH TETTEH, Ph.D. An Investigation of Analytics and Business Intelligence Applications in Improving Healthcare Organization Performance: A Mixed Methods Research. (2017)
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The healthcare ecosystem in the US is currently undergoing series of refinement and reformation due to the need to (i) improve quality of care and (ii) reduce cost. To achieve their key objective, healthcare organizations (HCOs) currently face a fundamental challenge: how to best use or optimize limited resources while providing better care and services to patients? The answer to this question might lie within HCO's massive data and the ability to identify and apply appropriate analytics and business intelligence (A&BI) techniques and technologies to discern and extract relevant information and knowledge from that data.

However, despite the increasing interest in the implementation and utilization of A&BI techniques and technologies by various organizations to improve operational efficiencies and financial performance, HCOs still lag behind other sectors in the adoption and use of A&BI capabilities. Motivated by the "data rich but information poor" syndrome currently facing HCOs, this dissertation applies a mixed method research–case study (interpretivist) and survey (positivist) – to investigate how healthcare organizations can leverage A&BI techniques and technologies to improve their overall performance.

In achieving this objective, I illustrate an exemplar of how A&BI techniques and technologies can effectively be applied by specifically answering this high-level research question (RQ): How can A&BI techniques, methods, and technologies be developed and leveraged to improve performance in healthcare organizations? This high-level RQ has

been broken down into four sub-questions that will be answered in two different studies in this dissertation. In the first study, I investigate what combination of A&BI techniques and technologies HCOs are currently applying to create value. This study was conducted by using content/literature analysis and case study methods in a large healthcare organization. The second study builds on the first study to investigate, using both interview and survey data, how A&BI capabilities can be developed, cultivated and nurtured as a core competency or capability that significantly helps improve healthcare organizations' overall performance (such as cost reduction, quick access to providers and treatment, effective diagnostics, etc.).

I found very novel and interesting results in both studies that not only address the research questions, but also provide significant theoretical and practical contributions. Major contributions of study 1 include: revising and remodeling of an outdated healthcare value chain (HCVC) framework that is more realistic and applicable to current care delivery practices in the healthcare industry and mapping of A&BI capabilities to the different domains of the revised HCVC framework. Study 2 provides theoretical contribution to the existing literature by conceptualizing and empirically validating A&BI capability as a third-order multi-dimension construct and its significant influence on performance.

AN INVESTIGATION OF ANALYTICS AND BUSINESS INTELLIGENCE

APPLICATIONS IN IMPROVING HEALTHCARE ORGANIZATION

PERFORMANCE: A MIXED METHODS RESEARCH

by

Rudolph Tetteh Bedeley

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To Mary,

Uriyella,

and Isabella Bedeley.

APPROVAL PAGE

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CHAPTER I

INTRODUCTION

1.1 Overview

Concerns about the quality of healthcare and economic sustainability of healthcare providers have existed for years all over the world (Dinev, T., Albano, V., Xu, H., and D'Atri, A., 2016). Government agencies and businesses who are involved in providing health coverage for workers and citizens have long called for cost control (Dinev et al. 2016). In the United States, a published report from the Business Roundtable, which represents CEOs of major companies, has concluded that the US healthcare system has become a liability that hinders companies' as well as healthcare organizations' competitiveness in a global economy (Alonso-Zaldivar 2009). As an additional twist, the report found that higher U.S. spending on healthcare fails to deliver a healthier work force, thus creating the largest "value gap" between cost and benefits among healthcare systems.

As part of the recovery interventions put in place to address some of these fundamental challenges facing the US healthcare system, the American Recovery and Reinvestment Act (ARRA) and the Health Information Technology Economic and Clinical Health (HITECH) Act were enacted to promote the use of Health Information Technology (HIT) programs (Henricks, 2011). Physician offices are given extra Medicare and Medicaid funds for achieving Center for Medicare and Medicaid Services

(CMS) metrics on quality of care and meaningful use measures. As of July, 2013, $9.5 billion was awarded for Medicare providers and $6 billion was awarded for Medicaid providers (www.cms.gov). Starting in 2015, eligible physicians that do not meet meaningful use with certified electronic healthcare records EHRs will see a 1% reduction in Medicare payments (Henricks, 2011). Until these metrics are met, payments will be reduced by an additional percent each year.

This major policy overhaul in the healthcare sector has drawn the attention of many healthcare providing organizations to seek better ways to re-engineering their current methods of operation. As a result, emphasis on the adoption and use of analytics and business intelligence (A&BI) tools and techniques has since been increasingly enforced by many healthcare organizations as one of the most efficient ways to streamline healthcare processes and operations in order to achieve better quality of care delivery and overall performance (Agarwal, Gao, DesRoches, & Jha, 2010; Chen, Chiang, & Storey, 2012). For example, Hanauer, Zheng, Ramakrishnan, and Keller, (2011) used large-scale, longitudinal EHR data to study associations in medical diagnoses and consider temporal relations between events to better elucidate patterns of diseases progression. Also, Lin, Brown, Yang, Li, Lu, and Chen, (2011) used analytics to study symptoms-disease-treatment (SDT) through association rule mining technique on a comprehensive EHR data of approximately 2.1 million records from a major hospital and discovered interesting patterns and relationships within the data.

Analytics and business intelligence (A&BI) are often used interchangeably to represent “systematic use of data to study potential trends, to analyze the effects of certain decisions or events, or to evaluate the performance of a given tool or scenario, with the goal of improving outcomes through greater knowledge" (Reiner 2013, p. 826). It draws on the knowledge and expertise of several disciplines (e.g. business, statistics, computer science, information systems, etc.) to derive business insight that results in evidence-based decision making for strategic planning, management, measurement and learning. Davenport (2013) classified the different types of analytics performed in every organization into one of these three categories: descriptive, predictive, and prescriptive. Descriptive analytics is the use of basic statistical techniques to provide descriptive analysis of what is evident from the data; predictive analytics is the type of analytics where future of a process, product, or activity can be predicted based on the result of the descriptive analytics; and prescriptive analytics is the type of analytics where the optimum output can be prescribed based on results of both descriptive and predictive analytics (Davenport 2013). A&BI techniques can be applied in healthcare organizations or hospitals to analyze all kinds of healthcare data that may be in the form of structured, semi-structured, and/or unstructured in search of valuable business information or hidden insight (Wang, Kung, & Byrd, 2016).

While there have been several studies on the adoption and impact of A&BI on organizational performance in many industries, the impact of analytics in the healthcare sector still remains an area of extremely high and untapped potential (Agarwal et al, 2010; Reiner 2013; Sharma, Mithas and Kankanhalli 2014; Wang et al. 2016). Thus, there has been paucity of IS research on A&BI impacts on performance in the healthcare sector although the McKinley Global Institute (MGI) estimates that healthcare big data analytics (i.e., analysis of large datasets) could save the U.S. healthcare system 300 billion dollars annually, with two thirds of that saving in the form of decreasing expenditures by 8 % (Gartner 2012; Reiner 2013).

1.2 Research Motivation

Until recently, accessibility and sharing of information between various departments within healthcare organizations have been very challenging as a result of lack of integrated systems to serve as central repository for all the organizational data (Armitage, Esther, Nelly, & Carol, 2009). Traditionally, data and information used to be created, owned and stored in silos by various departments with the goal of being in compliance with organizational and federal regulatory requirements put in place to ensure that patients data and information are well protected and secured (Suresh 2016). Due to the nature of complexity in data management, healthcare organizations face potential ethical, legal, and regulatory challenges such as data governance (Phillips-Wren, Iyer, Kulkarni and Ariyachandra 2015). However, research has shown that adopting suitable policies, standards, and compliance requirements to restrict users' permission to data, will lead to improved access and sharing which, in turn, can result in better efficiencies and improved care (Wang, et. el., 2016). Thus, integrated health systems are widely considered to provide superior performance in terms of quality and safety as a result of effective communication and standard protocols (Gillies, Chenok, Shortell, Pawlson and Wimbush, 2006).

Recognizing the importance of the information access and sharing in healthcare, and the slow rate of IT adoption in this sector (Angst and Agarwal 2006), governments, policy makers, advocacy groups, and individuals have invested extensive efforts to promote more rapid digitization and sharing of medical data (Anderson and Agarwal 2011). In the United States, the recently adopted stimulus package dedicates $50 billion over 5 years to spur the adoption of electronic health record (EHR) and electronic medical record (EMR) (Dinev et al. 2016). In November 2005, the U.S. Senate unanimously passed the Wired for HealthCare Quality Act (S. 1418), a bill to enhance the adoption of a nationwide health information technology (HIT) and to improve the quality and reduce cost of healthcare (Dinev et al 2016).

Such reforms and changes in the US healthcare delivery processes, have led to renewed interest in data-driven methods for delivering quality of care (Suresh, 2016) and performance improvement (Simpao, Ahumada, Galvez and Rehman 2014). Over the years, there has been progressive increase in the adoption and implementation of healthcare information technology (HIT), resulting in the generation of huge variety of patient data that comes from medical records (e.g. EHRs, biomedical data, etc.) as well as external data sources, such as insurance claims/billings, R&D laboratories, and social media data (Ward, Marsolo, and Froehle, 2014). Such proliferation of large-scale data has caught the attention and interest of many healthcare organizations towards making huge investments in A&BI techniques and applications to facilitate the extraction of valuable insights, making timely decisions, minimizing patient risk, and reducing clinical costs (Chen et al. 2012; Raghupathi & Raghupathi, 2014).

A&BI has a broader reach and scope than it is defined in Reiner (2013) study. It basically encompasses the use of various sophisticated analysis methods, such as statistical models and data mining algorithms for exploring data, quantifying and explaining relationships between measurements, and predicting new relationships (Shmueli, Bruce and Patel. 2016). According to studies by Gartner (2012, 2014), A&BI is now one of the top priority of chief information officers and primary area of technology investment in most healthcare organizations. A&BI is not entirely a new concept or technique to the healthcare industry as most healthcare organizations began adopting and implementing this technique dating back to the early 1960s (Goldschmidt, 2005). Today, many companies including healthcare organizations have been implementing A&BI tools and techniques in order to enable them analyze and process their constantly growing data (Suresh 2016). Owing in large part to such a heightened attention, A&BI has now become an important inclusion to increase value chain capabilities of many business organizations of which the healthcare industry is one major key beneficiary (Gartner 2012; Chen et al., 2012).

As an example, a major healthcare organization with 11 hospitals and 108 locations serving nearly 700,000 people in a large city in the US is currently deriving huge value from the implementation of A&BI techniques (HealthCatalyst 2016). As per Accountable Care Organization (ACO) new regulations, these healthcare organizations needed to deliver superior clinical outcomes, improve patient experiences, and enhance the affordability and sustainability of its services. Analyzing data in search of valuable clinical and business insights is an important part of the organization's long-range strategy for achieving these goals. For several years, leaders and management of healthcare organizations had prioritized A&BI as a key component of their strategic plan, but are yet to find an effective and comprehensive A&BI related systems and techniques for analyzing their data to enable them consistently improve their overall performance and deliver greater value to patients and stakeholders (HealthCatalyst 2016).

1.3 Research Gaps

A systemic review of the extant literature reveals that several current studies have proposed models, typologies and domains to study the impact of A&BI on organizations (Chen et al. 2012; Holsapple, Lee-Post and Pakath 2014; Wixom, Yen and Relich. 2013). Other studies have focused on the supply chain analytics capabilities (Chae, Olson and Sheu 2014) of organization from a resource-based view (Barney 1991) and dynamic capabilities perspectives (Eisenhardt and Martin 2000; Chae and Olson 2013). Whiles these studies have generally shown that relationship exist between A&BI adoption and organizational performance (operations, financial, etc.), there is – to the best of our knowledge – no study that has yet systematically investigated or shown how A&BI is being utilized in a large healthcare organizations to improve overall performance.

Unlike other industries, such as financial, retailing, telecommunication, etc., the healthcare industry currently lags behind significantly in taking full advantage of current and emerging state-of-the art A&BI tools and techniques (Ferranti, Langman, Tanaka, McCall, & Ahmad, 2010). Thus, many healthcare organizations are struggling today with the implementation of A&BI techniques and technologies even though they invest in numerous analytics systems and applications with the hope of achieving major transformation in their daily care giving activities (Murdoch and Detsky, 2013; Shah and Pathak, 2014). Moreover, evidence from a survey also shows that 60% of healthcare organizations surveyed fail to develop a clear, integrated enterprise strategy and vision for analytics deployment across a broad range of functions (Deloitte Center for health Solutions, 2015). One of the reasons for this lack of interest in A&BI implementation in healthcare organizations might be attributed to the lack of understanding of the economic potential of A&BI use (Groves, Kayyali, Knott, and van Kuiken, 2013; Murdoch and Detsky, 2013).

Evidenced by the above gaps, I conclude that the current stream of research on A&BI has focused mainly on addressing A&BI implementation issues pertinent to most industries. However, research on A&BI implementation in healthcare is significantly lacking and as such, healthcare organizations are currently in their early stages and lag behind other industry players due to lack of enough research in literature addressing fundamental managerial challenges related to A&B adoption that pertains specifically to healthcare (McAfee and Brynjolfsson, 2012), issues related to strategic choices and resource configurations (Xu, Frankwick, and Ramirez, 2016), and issues related to comprehensively understanding the managerial, economic, and strategic impact of A&BI (Raghupathi & Raghupathi, 2014;Ward et al., 2014). I further argue, therefore, that without reasonable guidelines backed by theory, not only is it difficult to help healthcare practitioners focus priorities and efforts on deriving value from A&BI adoption, but they also cannot find sufficient evidence of how A&BI investment can pay off (Murdoch & Detsky, 2013; Shah and Pathak, 2014).

1.4 Research Questions

Given this gap, and still limited understanding of the business value of how A&BI implementation in healthcare organizations can help improve performance, this research is being conducted to address the following key research question:

> **how can A&BI techniques, methods and technologies be effectively applied to improve overall performance in healthcare organizations?**

This higher-level research question has been broken down into sub-questions that will be addressed in two different studies:

Study 1:

1) Which A&BI tools and techniques are healthcare organizations currently implementing within the different domains of their value chain network to create value?
2) How are these A&BI systems and applications being applied in the various domains of the value chain in healthcare organizations?

Study 2:

3) What are the building blocks of A&BI capability in healthcare organizations?
4) How is this A&BI capability developed within healthcare organizations?
5) What are the impacts of this A&BI capability on healthcare performance?

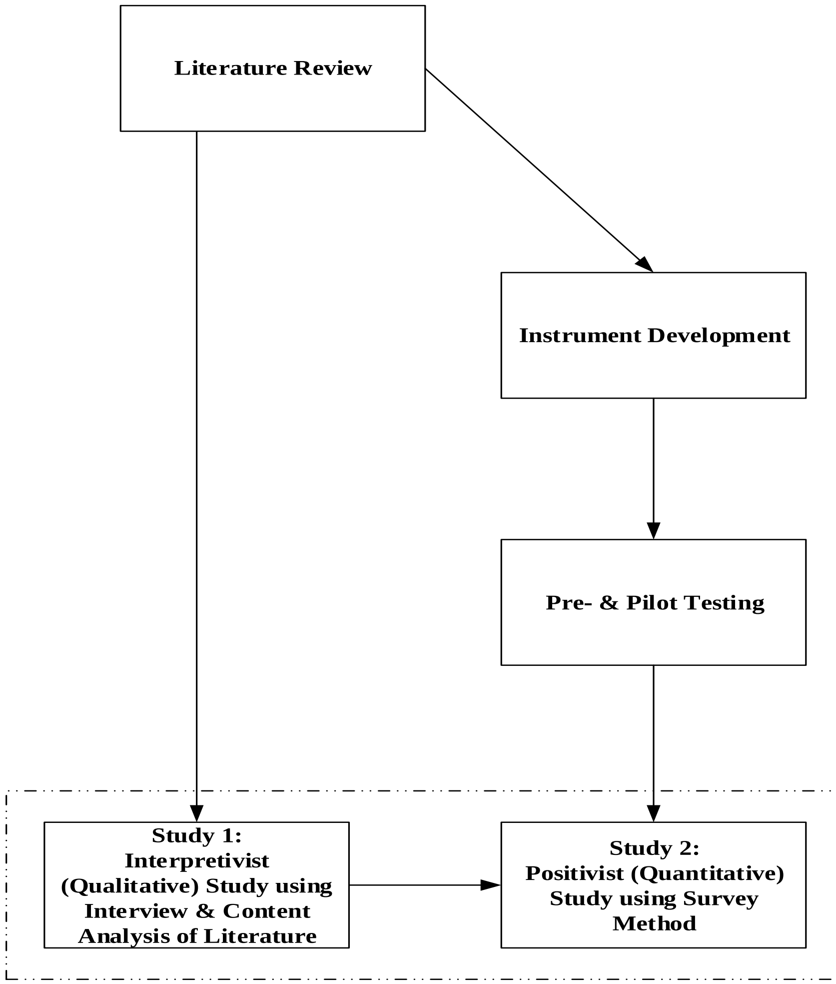

Figure 1. Research Approach

1.5 Research Approach

To address these research questions, I use a combination of qualitative research methods including content analysis of the literature, case study (interviews), and a quantitative study (survey) techniques. Figure 1 above presents a summary and schematic diagram of the research approach. Research questions in Studies 1 & 2 were addressed mainly through the use of both content analyses through extensive review of literature and interviews with BI directors, Top level management, IT employees, physicians, nurses and other business unit employees who utilize some kind of A&BI tools or technique. The content analysis complemented by interview data help provide rich and more granular insight in answering the first two research questions in Studies 1.

For the case study, used the methodology outlined by Yin (2009). I used an interpretive approach to this study in order to arrive at a richer and granular understanding of A&BI tools and techniques currently being used in healthcare organizations (Klein and Myers, 1999). I also used theoretical frameworks discussed in the later sections of this research to help guide the research design so as to gain appropriate insights from the rich primary data collected through interviews and surveys (Walsham, 2006). Case studies provide a deeper understanding in the healthcare context. For instance, Oborn, Barrett, and Davidson (2011) performed a single case study on cancer center. Goh, Gao and Agarwal (2011) also ran a single case study of a hospital exploring HIT influences on works routines. Kealy and Stapleton (2011) used multiple cases to study telemedicine projects in conflict areas.

To address research questions in Study 2, I used positivist research approach where I basically developed a research model that was mainly grounded in the literature and empirically tested this model using survey data collected from healthcare organizations.

1.6. IRB Exemption

An application for Institution Review Board (IRB) Exemption was submitted to the Office of Research at the Healthcare Organization participating in this study. The

Healthcare Organization has already granted the approval as it was determined to pose "no more than minimum risk to human subjects.

CHAPTER II

LITERATURE REVIEW AND THEORETICAL BACKGROUND

This chapter provides general background, comprehensive review of the existing literature, and a brief overview of theoretical foundation for the entire dissertation. Any detailed review pertaining to each of the various studies of the dissertation is provided in relevant sections.

2.1 Background

The healthcare ecosystem in the US is currently undergoing series of refinement and reformation by two opposing economic forces namely: (i) quality of care improvement, and (ii) cost reduction, as there is an ongoing pressure on healthcare organizations to do more with less (Suresh 2016; Wang et al., 2016). In order to achieve this fundamental objective (i.e. doing more with less), any healthcare organization with a vision for the future currently faces a fundamental question: *how to best use or optimize limited resources while providing better care and services to patients*? The answer to this question, according to prior studies, lies within healthcare organizations' data (Batarseh and Latif 2016; Suresh, 2016; Wang et al. 2016).

Healthcare organizations are seeking effective IT artifacts that will enable them to consolidate organizational resources to deliver high quality patient experience, improve organizational performance, and even create new, more effective data-driven business models (Agarwal et al., 2010; Goh et al., 2011). Clinical, administrative, and other healthcare related data hold the key to transforming healthcare systems by providing a greater insight to patients, providers, and policy makers on the appropriate quality and cost of care interventions (Institute of Medicine, 2010). As a result, the healthcare system original model is constantly evolving into "information driven", "evidence-based" and "outcome-driven" approach (Kalakota 2013). Using technology effectively and managing the overwhelming quantity of healthcare data to derive new information are now at the forefront of change in many industries but not as much in healthcare organizations (Gartner 2012; Wang et al. 2016).

Given that healthcare data is currently growing at such an exponential rate, there is a great opportunity to accelerate progress on the six characteristics of quality care which the healthcare system is expected to deliver. These characteristics, according to Institute of Medicine (2010); and Bloomrosen, Safran, Hammond, Labkoff, Tang and Detmer, (2007), include the following:

1. *Patient centered care*: designing and carrying out care systems that revolve around the patient, respect patient preferences, and put the patient in control of their health;
2. *Safe*: care provided to patients should be as safe in the care facilities as in their homes;
3. *Effective*: care provided to patients should strictly adhere to scientific principles and serve as the standard in the delivery of care;

4. *Efficient*: care and service should be cost effective to both patients and providers, and waste should be avoided in the process as possible;
5. *Timely*: unnecessary wait times and delays must be avoided during the processes of providing care and services to patients.
6. *Equity*: fairness in providing care to patients should be the ultimate goal of every provider. Thus, unequal treatment and discrimination should vehemently be discouraged.

Addressing the above important elements of quality care requires deep understanding of the scope and potential opportunity. This demands a great deal of knowledge of existing healthcare data (i.e. disparate data sources, types, accessibility, and use) (Institute of Medicine 2010). The combination of clinical and administrative data is a great and crucial resource. Currently, healthcare organizations are flooded by "tsunami" of data that can provide the potential to transform healthcare delivery and performance (Wickramasinghe and Schaffer, 2006; Smith, Drake, Harris, Watson, and Pohlner, 2011).

However, data that has not been processed or analyzed is neither an information nor knowledge until it is subjected to processing and refinement (i.e. manipulation of items of data) to produce information (French 1996; Smith et al., 2011). This therefore call for a combination of robust information technology infrastructure, technology expertise, and domain knowledge in information processing to perform the data "slicing and dicing", aggregation, analytics, visualization, interpretation, and presentation in order to produce reasonable information and generate the needed knowledge that is required to contribute to informed decision-making in healthcare services and policies (Smith et al., 2011).

Despite the great abundance of data and the limitless opportunities that comes along with it, many healthcare organizations currently lack the expertise, appropriate technologies, and key business management processes or techniques (such as analytics and business intelligence, data mining and machine learning, knowledge management, intuitive reporting systems, etc.) needed to maximize this invaluable resources (Wickramasinghe and Schaffer, 2006; Wang et al., 2016). Hence, this study is being conducted to bridge the gap by identifying the different combinations of A&BI techniques, technologies and expertise that healthcare organizations need to improve the quality of their care outcomes.

2.2 Literature Review

Unlike other industries such as finance, retails, telecommunications, manufacturing, etc. that have been far more advanced by successfully harnessing business value from large-scale integration and analysis of their organizational data (Groves et al. 2013), healthcare organizations are now beginning to get “their feet wet” (Shah and Pathak, 2014). Although the sector is widely known to be “inherently data-rich industry” (Pfizer and NCAQA, 2009), healthcare organizations are often referred to by their “data rich but information poor” nickname (Goodwin, 1996). Thus, only a fraction of the overwhelmingly abundant healthcare data is currently being utilized for analysis and reporting, leaving a great deal of information to rest at the core of healthcare.

However, effective exploration of healthcare data to derive meaningful insights, well managed and easily accessible timely information is fundamental to the future of medicine, improvement of patient care outcomes, and cost containment (Pfizer and NCAQA, 2009).

One promising breakthrough is the application and effective use of A&BI techniques and technologies (Gartner 2012; Wang et al. 2016). Analytics may be descriptive, predictive or prescriptive (Bedeley, Ghoshal, Iyer, Bhadury, 2016; Davenport, 2013). It enables healthcare organizations or hospitals to analyze a set of structured, semi-structured, and unstructured patients' data in search of valuable business information and insight (Gartner, 2013; Halaweh and Massry, 2015).

Transitioning to the use and advances in information technology in healthcare have resulted in the massive generation of "big data". In healthcare context, big data can be defined as a very large volume of clinical, financial, administrative, and other related healthcare data. Specifically, big data in healthcare would include data from the following sources: EHR; patient registry; CPOE systems; CDS systems; Ambulatory and emergency care records; physicians' written notes; prescriptions; medical imaging results; laboratory values; pharmacy records; insurance claims data; administrative data; and machine generated/sensor data.

While having lots of data can be very advantageous, data in its raw state or without context has no value on its own until it is processed. Without context, raw data is nothing but meaningless cluster of numbers, letters, or words (Philips, 2012). Processing raw data in order to transform it into insightful information requires a team of experts with domain knowledge and core A&BI skills of information systems, business, computer science, analytics and statistics, as well as strong communication skills (Moore-Colyer, 2014). Dataset needs to be identified from all possible sources, extracted, transformed, and analyzed using techniques that provide answers to a specific set of questions.

These basic steps alone pose a significant challenge in healthcare industry as healthcare organizations find it difficult to even identify and point to relevant and contextual data that can deliver value (Wang et al. 2016). Basically, healthcare organizations find it challenging to find insight within the "tsunami" of data they possess (Philips, 2012). Other possible impediment to data management in healthcare include: data volume, velocity, variety, variability, veracity, and value (Halaweh and Massry, 2015; SAS Institute, 2016). The complexity in healthcare system coupled with lack or limited data governance measures within and across healthcare organizations are also significant contributors to the challenges currently facing the healthcare sector. Moreover, another challenge is the inadequate accessibility to raw data for utilization in analytics because of vendor restrictions, silos of data, proprietary databases, and lack of data integration or appropriate data stores (Wang et al. 2016).

2.2.1 Lack of A&BI Capabilities in Healthcare

Despite the availability of massive data in data repositories, data warehouses, or data marts, healthcare data often remains unanalyzed and improperly reported to stakeholders for the necessary informed decision that generates actionable outcome to be made. Thus, healthcare organizations face myriad of challenges in their deployment and use of A&BI techniques and technologies (Sharma et al., 2014). These include insufficient resources, inadequate technological infrastructure, and lack or limited understanding of the application of analytics to business, quality issues, and performance goals across organizations and stakeholders. Technologies must be evaluated for interoperability and compatibility, and for measures that are necessary in data standardization for future data utilities (Grossman, Goodby, Olsen, and McGinnis, 2010).

In order to harness A&BI potentials, investments may be required to develop linkages across the source systems and data warehouses to leverage access to both administrative and clinical data (Grossman et al., 2010). Human resources or human capital is another aspect of A&BI that healthcare organizations needs to invest more in as there has been a limited supply of A&BI talent in the industry at large. Although A&BI tools, technologies, and infrastructure are indispensable, the right people with deep understanding of the business needs, desired goals, and objectives are equally crucial for the success of analytics deployment. People with analytics talents/knowledge capable of deploying their knowledge, skills, and the appropriate tools are needed to provide relevant and current information to decision makers and other stakeholders at all levels in the organization.

Moreover, the lack of appreciation of the importance of an A&BI team can be another potential source of challenge. This is due to the fact that many healthcare A&BI teams become overwhelmed by lots of requests for a variety of reports, dashboards, and other A&BI applications. Consequently, the team becomes too involved in information development requests from users rather than focusing on enhancing the A&BI infrastructure and developing new tools of tactical and strategic significance (Strome, 2014). Lastly, healthcare A&BI is often impeded by regulatory concerns, resource constraints, and more importantly, organizational cultures that are slow to trust and embrace the role and importance of analytics (Ferguson, 2013).

2.2.2 The Need for A&BI in Healthcare

The relatively recent changes in healthcare delivery processes and expectations (e.g. Patient Centered Medical Home, Pay-For-Performance, and Accountable Care Organization) has drawn the attention of all stakeholders to the need for embracing state-of-the-art technologies that facilitate easier retrieval, analyzing, and tracking of patient data with a focus on improving patients' care. To address healthcare inefficiencies and information deficiencies, leading healthcare organizations have begun implementation of data repositories to aggregate clinical data, as well as building data warehouses to support the A&BI needs of various initiatives, mandates, and programs, such as evidence-based practices, performance monitoring, quality improvement initiatives, outcome-based reimbursement models, etc. (Biesdorf and Niedermann, 2014).

However, the ability to apply appropriate A&BI techniques and technologies to derive insights from the progressively growing patient demographics, progress notes, problems, medication, vital signs, past medical history, immunization, laboratory data, and radiology reports, etc. is currently the main challenge facing many healthcare organizations (Chen et al. 2012; Wang et al. 2016; Sharma et al., 2014).

2.2.3 The Evolution of Digitization in Healthcare

The first wave of information technology use in healthcare began in the 1950s when the emphasis of IT use was mainly on the business and administrative side of healthcare using technology for the automation of repetitive tasks such as accounting and payroll (Cresswell and Sheikh, 2013). Healthcare organizations and other industry stakeholders began to use IT to process vast amounts of statistical data. The initial digitization phase of an industry is designing and using systems that specifically support transaction-based workflow and data collection.

The second wave of massive IT implementation in healthcare industry started twenty years later with the main focus on patient's medical record, which began with the use of electronic medical record (EMR) systems in place of paper charts (Biesdorf and Niedermann, 2014). EMRs contained the medical and treatment history of patients in a single practice. The main advantages of EMR over paper based record keeping include the ability to track patients over time, to easily identify patients due for preventive screening, and to monitor patients on certain parameters such as blood sugar level, vaccination, etc. However, EMR is not without setbacks as one of its major drawbacks include: inability to maintain longitudinal medical records of patients being cared by multiple care providers (Clayton, 2005); limited ability to support coordination between clinicians and settings due to their design and lack of standardization of key data elements required for information exchanges; difficulty in management of information overflow; inability to adequately capture the medical decision making process and future care plans for care coordination; not designed for non-billable care coordination activities but rather for fee-for-service billable events (i.e. office visits, procedures, etc.) (O'Malley, Grossman, Cohen, Kemper, and Pham, 2010).

The third wave of healthcare digitization, which is gradually becoming popular in the past decade, basically focuses on the analysis of different aspects of data, information, and workflow that are reflected in the patterns of aggregate data in order to provide value. This phase of information technology focuses on the utilization of data to improve care. Without a way of organizing the clinical, financial, administrative, and other healthcare related data into a single source of truth, a healthcare system cannot extract value from their data. In order to gain actionable clinical, financial, and operational insights, data from EMR, EHR, and other related internal and external source systems, data must be captured, aggregated, analyzed, and presented in meaningful way (Biesdorf and Niedermann, 2014). This phase is characterized by the implementation and adoption of data repositories for aggregation of clinical data and building electronic data warehouse.

2.2.4 Healthcare Information Technology (HIT)

As part of the strategic initiatives to improve care outcomes, healthcare organizations are investing heavily in the implementation of healthcare information technology (HIT), which is defined as the “array of devices, procedures and processes for collecting, referencing and/or managing health information electronically” (Pfizer and NCAQA, 2009). HIT enables healthcare organizations to access and updates healthcare information to support both clinical and administrative side of care facility (Goldschmidt, 2005; Goldzweig, Towfigh, Maglione, and Shekelle 2009; Menon, Yaylacicegi, and Cezar, 2009). HIT encompasses broad categories of technologies including: electronic medical record (EMR), electronic health records (HER), e-prescribing, computerized physicians order entry (CPOE), clinical decision support (CDS), telemedicine, advanced medical imaging, smart pumps, bar coding devices, etc. (Eastaugh, 2012; Goldschmidt, 2005; Gupta 20016; Landro 2004). HIT offers improvement by augmenting decision-making for healthcare professionals and assisting healthcare staff in patient care. Healthcare professionals, particularly physicians, are struggling with information overload. It is beyond human capability to continuously learn, remember, and apply the mounting evidence and the knowledge that is being generated on a daily basis. HIT aims to compensate for human limitations, enhance decision-making, improve delivery of care, and offer value for patients.

The healthcare sector is information-intensive industry as large percentage of its activities are enabled by the storage, processing, transfer, and analysis of data (Divev et al. 2016). As such, quick access to patients' medical record, which is often streamed from various sources, can lead to a significant reduction in medical errors, help in performing effective diagnosis, and facilitate the communication with related agencies and businesses (Gupta et al. 2016). Electronic forms and data management, electronic prescription filing, and electronic managed care contribute significantly in increasing healthcare quality and safety, cut costs, and improve efficiency and precision of diagnosis and operation (Divev et al. 2016; Gupta et al. 2016). Thus, digitizing patient records is an essential part of the HIT overhaul initiated purposely for improving quality of care whiles minimizing cost at the same time. Healthcare data are mostly generated from two main sources: (i) genomics-driven data (e.g. genotyping, gene expression, sequencing data) and

(ii) payer-provider data (e.g. EHR, EMR, insurance records, pharmacy prescription, patient feedback and responses) (Miller 2012).

Over the past decades, EHR have widely been adopted in hospitals and clinics throughout the entire country. Angst and Agarwal (2006) defined EHR as “a software system that healthcare providers use to create, store, update and share patient information in electronic format” (p. 20). Significant clinical knowledge and a deeper understanding of patient disease patterns can be gleaned from the implementation of EHR (Hanauer, Rhodes, and Chinnaiyan, 2009; Hanauer, et al. 2011; Lin, Brown et al. 2011). For instance, Hanauer et al. (2011) used large-scale, longitudinal EHR to study associations in medical diagnoses and consider temporal relationships between events to better identify patterns of disease progression (Chen et. al. 2012).

Venkatraman, Bala, Venkatesh, & Bates (2008) defined EMR as “an automated clinical system that generally includes data related to medical history, patient demographics, clinician’s notes, drug information, electronic prescriptions and diagnostic test orders” (p. 140). Basically, EMRs are designed to follow a patient with regard for location (Williamns & Boren, 2008; Dey, Sinha, and Thirumalai 2013). For instance, a patients’ EMR can be reviewed by their primary physician and any number of specialists even if they are not physically present in the same location. Thus, there are no standards with these records as each application is tailored towards individual practices and as such, it becomes difficult to transfer records between offices with applications from different vendors (Venkatraman et al., 2008; Hoffman, 2009). In some hospitals, different departments will utilize EMRs from different vendors (Venkatraman et al., 2008). In addition to the issue of standardization, Hoffman (2009) wrote that there were other challenges to EMRs: i) the challenge of adoption and ii) compliance issues. While most physician offices will foot the cost of the system, they don't often realize the benefits of adoption. Instead, insurance companies benefit through cost savings such as reduction in duplicated tests for individual patients. The second challenge, which is associated with compliance issues, comes about as a result of conflict with Health Insurance Portal and Accountability (HIPAA) statues and the variances in different state regulations surrounding medical privacy.

Quite recently, the Healthcare Information Technology for Economic and Clinical Health (HITECH) Act was introduced with a provision of thirty billion dollars to promote "meaningful use" of EHRs through the Medicare and Medicaid EHR incentive program (Blumenthal, 2010; Robert Wood Johnson Foundation, 2014). The fundamental objective of this incentive program was to "provide financial support for the hospitals in the form of payments for the meaningful use of health information technology through Medicare. Payments are made for adopting, implementing, or upgrading an existing EHR through the Medicaid program" (Robert Wood Johnson Foundation, 2014). However, just as it is with the introduction of any new system or technology, HIT is not without a challenge. Thus, the implementation of HIT is faced with a lot of challenges such as organizational, cultural, technological, sociological, and political. In other words, healthcare organizations are still struggling with the introduction of some new systems and technology, as a result of uncertainties surrounding performance limitations of the new systems/technologies (Friedman, Metzler, Detmer, Selzer, and Meara, 2012; Pfizer and NCAQA, 2009; Robert Wood Johnson Foundation, 2014).

2.3 Technology Impacts in Healthcare

In this section I present an overview from the literature on how technology is transforming the healthcare industry in the various areas of performance measures including: quality of care improvement, cost reduction, collaboration and communication, internal workflow, and overall performance.

2.3.1 Quality of Care and Cost Reduction

In their literature review of technology impacts on healthcare, Chaudhry, Wang, Wu, Maglione, Mojica, Roth, and Shekelle, (2006) separated the impacts into three main categories: quality, costs, and efficiency. In addition to these three categories, other studies have suggested that collaboration, communication, and internal work flow also contribute to successful implementation of technology in healthcare organizations (Wang et al. 2016).

Patient Quality of Care (QoC) impacts have been extensively examined by researchers in several ways. One is through digital reminders for medical adherence to ensure that patients are taking the needed medication in a timely manner (Chaudhry et al. 2006). Another indicator is the reduction in errors (Byrne, Mercincavage, Pan, Vincent, Johnston, and Middleton. 2010). Technology systems can help minimize these errors through decision support tools that alert physicians about drug interactions or allergy issues. Other studies have looked at quality of care through organizational compliance to treatments (Kane an Alavi, 2008; Perez-Cuevas, Doubova, Suarez-Ortega, Law, Pande, Escobedo, and Wagner, 2012). The last approach to measure QoC is through patient satisfaction.

Nowinski, Becker, Reynolds, Beaumont, Caprini, Hahn, and Arnold, (2007) conducted a longitudinal study of an EHR implementation within a large clinical network and examined how the EHR impacted both the organizational culture and the patients' quality of care. Kane and Alavi (2008) were interested in how user interaction with Health Information Systems (HIS) and IS centrality impacted both quality and efficiency of care. Byrne et al. (2010) used secondary data between 2003 and 2007 to examine the rate of IT adoption and IT spending and their impact on QoC. Perez-Cuevas et al. (2012) more recently studied four large family practices in Mexico City and examined how the EHR systems can be used to measure patients' quality of care. Bardhan and Thouin (2013) studied the impact of Clinical Information Systems (CIS) on both quality of care and costs. Table 1 below summarizes the findings and methodologies used in these studies on QoC.

Table 1. Summary of Studies about Technology Impacts on Quality of Care

Authors	Methodology	Findings
Nowinski et al. (2007)	Quantitative Survey	Organizations became more hierarchical after system implementation As work flows and processes were formalized, the organization's hierarchy became more entrenched Partial evidence of quality of care improvement Consultation turnaround times had improved
Kane and Alavi (2008)	Social Graph Analysis	User interaction had no impact on either efficiency of care or quality of care IS centrality reduced the wait time for patients and had a positive impact on quality of care
Byrne et al. (2010)	Quantitative Secondary Data	VA hospitals have had a 100% HIT adoption since 2004 vs non-VA hospitals with 61% for EHR

		adoption, 16% CPOE adoption, and 12% EMR adoption VA hospitals had higher IT spending and a larger impact on Quality of Care
Perez-Cuevas et al. (2012)	Quantitative Patient Data	EHR system data could be mined to monitor the quality of care for type 2 diabetes Using EHR patient data, recommendations could be made for improving treatment in those practices
Bardhan and Thouin (2013)	Quantitative Secondary Data	Positive correlation between CIS usage and treatment Greater impact on process quality within not-for-profit and urban hospitals compared to for-profit hospitals Greater reduction in costs within for-profit hospital compared to the other two categories

2.3.2 Collaboration and Communication in Healthcare

Technology is the engine of change that has set the stage for an unprecedented transformation in healthcare (Harington, 2014). The impact of technology on healthcare can be realized through effective task execution as manifested in intensive intra- and inter-organizational collaboration and communication. In addition to the summarized internal communication, example of external communication could be as simple as healthcare providers sending prescriptions to pharmacy or as complex as getting a patient's records from a local hospital. The question then becomes: how are healthcare organizations using technology to facilitate external communications and interactions through sharing of inter-organizational information?

Beuscart-Zéphir, Pelayo, Anceaux, Meaux, Degroisse, and Degoulet (2005), through a multiple case study, examined the implementation of Computerized Physician Order of Entry in hospitals and how that implementation impacted the interactions between nurses and doctors. Oborn et al. (2011) performed a single case study on cancer center to examine their EMR usage and how it impacted the interaction between doctors of different disciplines. Table 2 below provides a summary of the findings and the methodologies used in these studies.

Table 2. Technology Impacts on Collaboration & Communication Study Examples

Authors	**Methodology**	**Findings**
Beuscart-Zephir et al. (2005)	Multiple Case Studies	With the CPOE implementation: • Little to no collaboration • Errors occurred due to misinterpretation of orders
Oborn et al. (2011)	Single Case Study	Despite unique uses amongst specialists, the system was capable of supporting coordination between individual specialists.

2.3.3 Internal Workflow

Technology facilitates internal work flow processes in healthcare organizations by tracking how members of a healthcare organization perform their duties (Aarts, Ash and Berg 2007). An example can be transfer of duties from one group of staff to another (Aarts et al., 2007; Lichtner, Venters, Hibberd, Cornford, and Barber, 2013), another example can involve monitoring the progress or efficiencies within the practice that affect the entire staff (Aarts et al, 2007; Lahiri and Seidmann, 2012). Literature reveals that only one study has investigated how physicians took the initiative to somehow let information technology entirely guide their daily activities (Kane & Labianca, 2011).

Aarts et al. (2007) examined the effects of implementing CPOEs in hospitals with regards to workflow, system errors, and organizational culture. Their study also focused on CPOEs and its impacts on both quality of care and work flow. Kane and Labianca (2011) studied physicians' avoidance of a newly implemented EMR system in a large medical facility. In a single case study on Radiology Information Systems (RIS), Lahiri and Seidmann (2012) studied the impact on work flows. Lichtner et al. (2013) did a field study on four General Practitioner (GP) practices and how their use of an Electronic Prescription Service (EPS) impacted employee work load. Table 3 provides a summary of the findings and methodologies used in these studies.

Table 3. Studies that Examine Technology Impacts on Internal Work Flow

Authors	**Methodology**	**Findings**
Aarts et al. (2007)	Quantitative Survey & Follow-up Qualitative Interviews	• CPOEs impacted hospitals by: o creating more and new work o changing work flow o new system errors o creating shifts in power from physicians to staff • System slowed work processes when it was taken off line. • Many hospital staffs perceived increases in hospital efficiencies • Some staff members saw a decrease in work load that was shifted to the physicians
Aarts et al. (2007)	Qualitative Interviews	• CPOEs impacted both quality of care and work flow. • While most organizations did not see improvements, academic medical centers and the

		VA medical centers did observe some quality of care improvements • Most organizations saw negative impacts on their work flows
Kane and Labianca (2011)	Single Case Study	Patient care is negatively impacted when physician IS avoidance occurs at a bottleneck within the organization's work flow
Lahiri and Seidmann (2012)	Single Case Study	Hang over had a negative effect on the efficiency of care as providers had to take additional time to collect necessary data
Lichtner et al. (2013)	Qualitative Field Study	• Administrative paper work and repeat prescriptions took less time with the implementation of the system • Time was lost due to the slow response of the centralized messaging center. • While staff had less administrative work post implementation, physicians had an increased work load

2.3.4 Performance Outcomes

A group of studies that examined Performance Outcomes have focused primarily on financial performance (Kohli and Devaraj, 2004; Ko and Osei-Bryson, 2004; Thouin, Hoffman, and Ford 2008; Setia, Setia, Krishnan, and Sambamurthy 2011). Another group of researchers looked at operational performance. Dey et al. (2013) focused on hospital performance with regards to patient throughput. Ward et al. (2014) studied the impact on hospital stays and patient satisfaction.

Kohli and Devaraj (2004) studied the revenue impact of Decision Support Systems (DSSs) on healthcare organization revenue. Ko and Osei-Bryson (2004) examined the impact of IT investment on productivity in hospitals. Thouin et al. (2008) focused their study on financial performance of Integrated Healthcare Delivery Systems (IHDS). Setia et al. (2011) examined how IT was used within hospitals and how it impacted financial performance. Bourgeois, Denslow, Seino, Barber, and Long, (2011) studied how IT sophistication impacts financial performance, mortality, and safety. Dey et al. (2013) studied how EMR system capabilities impacted operational performance. Ward et al. (2014) performed a longitudinal study on the operational impact of an EHR system on a single Emergency Department (ED) in a suburban, academic medical center. Table 4 provides a summary of the findings and methodologies used in these studies.

Table 4. Summary of HIT Performance Outcome Studies

Authors	**Methodology**	**Findings**
Kohli and Devaraj (2004)	Quantitative Historical Data	DSS usage within hospitals had a positive impact on the revenue
Ko and Osei-Bryson (2004)	Quantitative Secondary Data	• IT investments alone do not have a positive impact on hospital productivity • Combined with other investments such as labor and non-IT capital, IT investments show a positive impact on hospital productivity
Thouin et al. (2008)	Quantitative Secondary Data	• Higher levels of HIT spending as well as higher levels of HIT outsourcing had a positive impact on the financial performance of IHDSs • No significant increases of financial performance due to increased levels of HIT staffing.
Setia et al. (2011)	Quantitative Secondary Data	• Only targeted use of business IT had a positive impact on the financial performance

		• Only wide use of clinical IT had a positive impact. • Long term use of both clinical and business IT had a positive impact.
Bourgeois et al. (2011)	Quantitative Secondary Data	• In small hospitals, IT sophistication only had a significant positive impact on safety. • In medium hospitals, IT sophistication had significant positive impacts on both safety and mortality. • In large hospitals, IT sophistication had a significant negative impact on safety while having a significant positive impact on mortality.
Dey et al. (2013)	Quantitative Secondary Data	Facilities with higher stages of EMR capabilities had a more positive impact on operational performance than facilities with lower EMR capabilities.
Ward et al. (2014)	Longitudinal Case Study	• A temporary increase in hospital stays and a decrease in patient satisfaction after the system were implemented. • Those changes did revert to pre-implementation levels eight weeks after implementation. • Significant increase in tests performed post implementation.

2.4 Overview of Theoretical Foundation

Study 1 of this dissertation draws on the concepts of Burns, DeGraaff, Danzon, P.M., Kimberly, Kissick, and Pauly (2002) healthcare value chain framework which was basically adapted from Michael Porter's (1985) Value Chain Framework to investigate how healthcare organizations are creating value through their primary and secondary activities. In the healthcare context, however, a more modified version of Porter's (1985) original value chain has proved useful in understanding how various activities tailored toward quality of care delivery fit together (Sastry 2014).

Porter (1985) introduced the concept of value chain with an idea that every organization has two distinct sets of activities to create value for the organization (Figure 2). One activity set is the primary activities involved in creating the physical product or service, marketing and delivery of the product or service, and support and after-sale service for that product or service. Another set is the supporting activities of the organization. The supporting activities are composed of internal activities of the organization which provide inputs and infrastructure to support the primary activities of the organization. Porter (1985) describes five primary activities as generic supply chain activities of organizations' value chain: Inbound logistics, operations, outbound logistics, marketing & sales, and after- sales service. The four supporting activities are: procurement, technology development, human resource management and firm infrastructure.

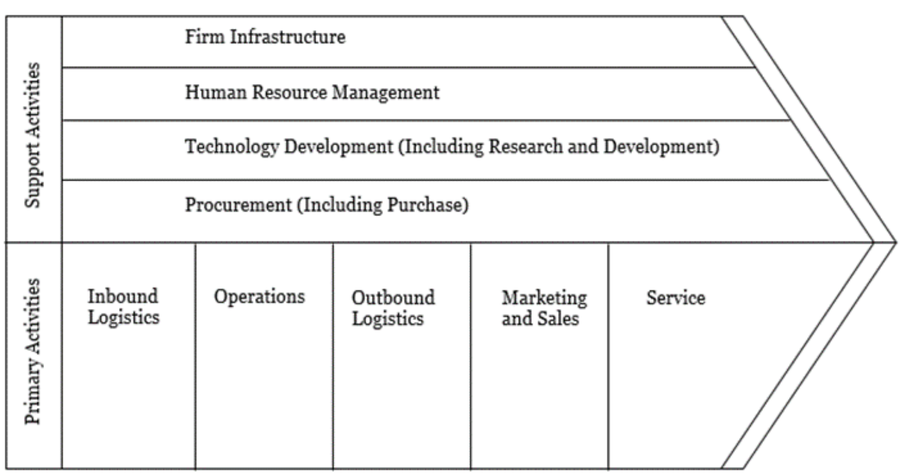

Figure 2. Porter's (1985) Value Chain Framework

Burns et al. (2002) later came up with a revised value chain framework specifically created for healthcare organizations (Figure 3). In the context of healthcare, the value chain framework redefined a reversed order in such a way that the support activities, which comprise of hospital support services; hospital diagnostic and therapeutic services; information services; and hospital administration, collectively form the foundation activities whiles the primary activities, which include admission; care; discharge; marketing and sales; and service constitute the front-end activities. Healthcare organizations depend on this configuration of value-chain mapping to figure out how to improve quality (or lower costs) of care by delivering or connecting patients to their services in order to fully benefit from the entire chain of activities needed for better care (Sastry 2014).

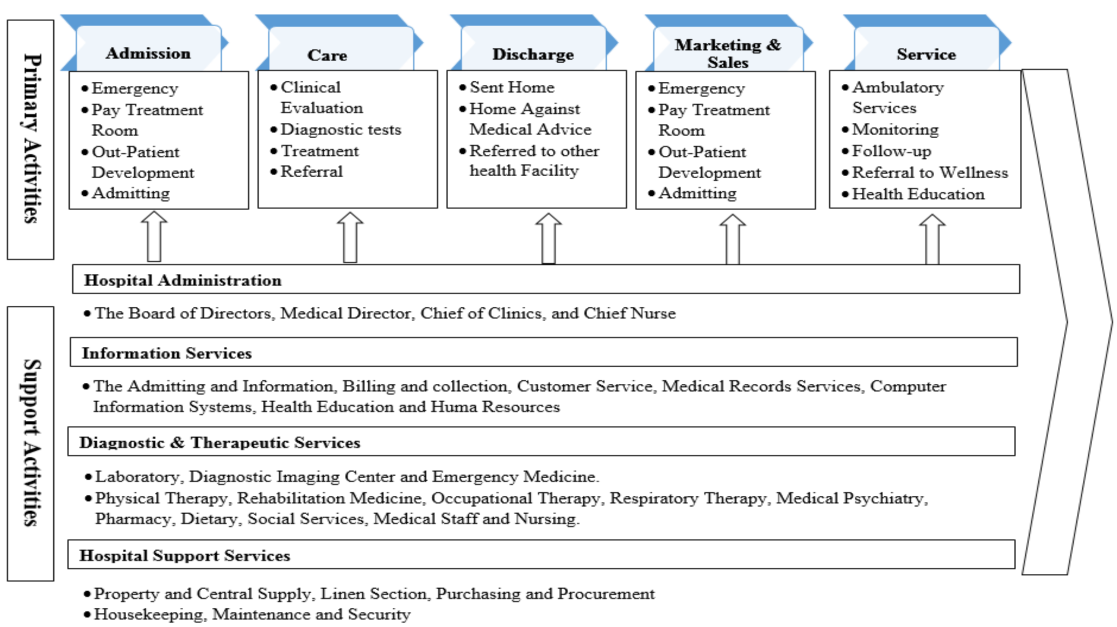

Figure 3. Value Chain Framework of Hospitals (Adapted from Burn et al. 2002)

These frameworks were used as the main theoretical lenses through which Study 1 was conducted. Thus, these frameworks were used as a guide to inform the design of interview questionnaires as well as data collection. In other words, the frameworks were used to identify which analytics techniques and technologies healthcare organizations are currently deploying and how these are contributing towards improving quality of care and overall performance or outcome.

Study 2 draws on multiple theoretical lenses including resource-based view (Barney 1991), IT capability (Sambamurthy and Zmud 1997), entanglement view of socio-materialism (Orlikowski and Scott 2008) and the strategic alignment (Henderson and Venkatrama 1999). These theories are elaborated in details under the Study 2 section of this dissertation.

CHAPTER III

STUDY 1: A&BI APPLICATIONS AND HEALTHCARE ORGANIZATIONAL VALUE CHAIN

3.1 Introduction

The healthcare sector has drawn the attention of many healthcare providing organizations to seek better ways to re-engineer their current methods of operation. As a result, emphasis on the adoption and use of information technology (IT) mechanisms as well as analytics and business intelligence (A&BI) systems, tools and techniques has since been increasingly enforced by many healthcare organizations as one of the most efficient ways to streamline healthcare processes and operations in order to achieve better quality of care and overall performance (Agarwal, et al. 2010; Chen et al. 2012). However, while there have been several studies on the adoption and impact of healthcare information technology on organizational performance, there is still paucity of research that have investigated IT-enabled A&BI impacts on healthcare value creation and delivery in the Information Systems discipline (Sharma, Mithas, and Kankanhalli, 2014; Wang, Kung, & Byrd, 2016).

In 2010, the Patient Protection and Affordable Care Act (ACA) was introduced purposely to accelerate the need for health IT by expanding healthcare coverage and implementing new models of care delivery aimed at creating patient-centric, value- based health system (Vicini and Stempel 2012). In an attempt to overcome the adverse effects of siloed care under the traditional fee-for-service reimbursement model of care giving, ACA introduced new value-based delivery models such as the accountable care organization (ACO) to improve quality and reduce cost. ACO is broadly defined as a group of providers that are integrated across disparate settings into a unified network (Foundation TKF 2013).

The ACO was introduced purposely to keep people healthy and away from coming to the hospitals for admissions and treatment. In an attempt to keep people healthy remotely through health IT-enabled applications and initiatives, healthcare organizations gain monitory incentives from insurance payments and avoid penalty payment to the government. This has resulted in many healthcare organizations revising and adopting IT-enabled service providing strategies. Their ultimate goal, however, is to become more proactive by reaching out to potential patients, engaging them by providing healthy living advice as well as other health services to help keep them healthy and avoid hospital visits.

Based on extant literature, healthcare organizational value creation and delivery has been studied under only one framework (see Figure 2) originally developed by Burns, DeGraaff, Danzon, Kimberly, Kissick, & Pauly (2002). This framework is more focused on hospital operations and other healthcare activities that result in value creation and delivery within the hospital environment. However, since the introduction of ACA and ACO, healthcare organizations are shifting their focus onto IT-enabled systems and processes to boost care delivery (Byrne et al. 2010; Pérez-Cuevas, Doubova, Suarez-Ortega, Law, Pande, Escobedo, and Wagner, 2012) and value creation (Bardhan and Thouin 2013; Lichtner, Venters, Hibberd, Cornford, and Barber 2013). This value creation initiatives are not only occurring within hospital premises but also by reaching out to people within their communities. As several healthcare providers were presented with Burns et al. (2002) framework and asked to share their opinion on how this framework is currently being applied to boost value creation, it became clear that the current framework is outdated and not sufficient anymore.

It is therefore in light of this paradigm shift in care delivery under the current ACA and ACO regulations that it becomes necessary that Burns et al. (2002) HCVC framework, which is almost 2 decades old, is thoroughly reexamined for its relevance and reliability. Based on this motivation, this study aims to understand the influence of IT-enabled A&BI systems and applications on healthcare organizations value chain activities by addressing the following key research questions:

i) what IT-enabled analytics and business intelligence (IT-enabled A&BI) tools and techniques are currently being implemented to drive value within the different domains of healthcare organizations value chain network? and

ii) how are these key IT-enabled A&BI systems and applications being leveraged or utilized in the various domains of the value chain in healthcare organizations?

To address these research questions, I use interpretive case study (Walsham 2006) method to explore and describe the case of a large healthcare organization with five smaller affiliate care giving organizations. I draw on interpretive sociology and organizations as interpretive systems literature to study healthcare organization views of the current value and relevance of the existing healthcare value chain framework.

This study contributes to existing literature by being the first to redevelop an updated HCVC framework which is more current and therefore expected to draw several research interests from various researchers. For example, the revised framework can be used to conduct several empirical studies to address how healthcare organizations are currently utilizing Health IT-enabled A&BI applications to create and deliver value for both the consumer and provider. Moreover, the revised HCVC framework contributes to healthcare practice by illustrating how health IT is currently transforming and reforming the current practices within the general healthcare ecosystem. This will help healthcare organizations consider re-strategizing and revising their existing approach to value creation and delivery to meet current practices.

The study is organized as follows. I begin by providing a background of this study which is grounded in Burns et al. (2002) healthcare value chain framework. I then describe the methodology where the case study is presented in detail. The study continues with a discussion of the findings and their implications for research and practice. The contributions and limitations of the research are then amplified in the concluding section of the paper.

3.2 Study Background

This study is grounded in both academic and practitioner literature in IS and healthcare IT with particular emphasis on healthcare value chain framework (Burns et al. 2002) and the Accountable Care Organizations Population Health Management (ACO-PHM) Framework, otherwise known as the *ACO-based PHM* pyramid. The healthcare ecosystem is being reshaped significantly by two powerful and opposing economic forces: (1) to improve quality of care, and (2) to reduce cost. As a result, there is pressing demand on healthcare providers to do more with less. In order to achieve this objective, any healthcare organization with a vision into the future face a fundamental question - *how to best to use limited resources while better managing patient care*?

The answer to this question probably lies within healthcare organizations' data and the ability to efficiently apply information technology techniques to create value out of their massive data. Thus, IT-enabled A&BI systems and applications hold the key to transforming the healthcare system, by providing greater insight to patients, providers, and policy makers on the appropriate interventions, quality, and cost of care (Institute of Medicine 2010). Based on this, the traditional healthcare delivery system is changing into "information driven," "evidence-based," and "outcome-driven" system (Kalakota 2013). Using technology effectively and managing the overwhelming quantity of data to derive new information are at the forefront of the change.

The recent changes in healthcare delivery processes and expectations (e.g. Patient Centered Medical Home, Pay-For-Performance, and Accountable Care Organization) have drawn the attention of all stakeholders to the need for embracing state-of-the-art technologies. The aim for investing in these new and emerging technologies and techniques is to facilitate easier retrieval, analyses, and tracking of patient data with a focus on improving care provided to patients (Wang et al. 2016). To address healthcare inefficiencies and information deficiencies, leading healthcare organizations have begun implementation of data repositories to aggregate clinical data and are building data warehouses to support the analytical needs of various initiatives, mandates, and programs, such as evidence-based practices, performance monitoring, quality improvement initiatives, outcome-based reimbursement models, etc. (Biesdorf and Niedermann, 2014).

However, the ability to apply appropriate analytics techniques and technologies to derive insights from the progressively growing patient demographics, progress notes, problems, medication, vital signs, past medical history, immunization, laboratory data, and radiology reports, etc. is currently the main challenge facing many healthcare organizations (Chen et al. 2012; Wang et al. 2016; Sharma et al., 2014).

Despite the rapid growth of data, healthcare organizations' data often remains unanalyzed and improperly reported to stakeholders for the necessary informed decision that generates actionable outcome. Healthcare organizations face myriads of challenges in their deployment and use of analytics and business intelligence (A&BI) systems, techniques and technologies (Sharma et al., 2014). These include insufficient resources, inadequate technological infrastructure, and lack of or limited understanding of the application of analytics to business, quality issues, and performance goals across organizations and stakeholders. In the following sections, I describe the two foundational frameworks that inform this study.

3.3 The Healthcare Value Chain Framework (HVCF)

This study draws on the concepts of Burns et al. (2002) healthcare value chain framework which was basically adapted from Michael Porter's (1985) Value Chain

Framework originally developed to investigate how healthcare organizations are creating value through their primary and secondary activities. In the healthcare context, however, a modified form of Porter's (1985) original value chain has proved useful in understanding how various activities tailored toward quality of care delivery fit together (Sastry 2014).

Porter (1985) introduced the concept of value chain in his book with an idea that every organization has two distinct sets of activities to create value for the organization (Figure 2). One activity set is the primary activities involved in creating physical product or service, marketing and delivery of the product or service, and support and after-sale service for that product or service. Another set is the supporting activities of the organization. The supporting activities are composed of internal activities of the organization which provides inputs and infrastructure to support the primary activities of the organization. Porter (1985) describes five primary activities as generic supply chain activities of organizations' value chain: Inbound logistics, operations, outbound logistics, marketing & sales, and after- sales service. The four supporting activities of organizations' value chain are: procurement, technology development, human resource management and firm infrastructure.

The healthcare value chain framework was introduced in the healthcare industry during the early 2000s as a result of several major developments such as vertical integration, horizontal integration, managed care pressures, changes in federal reimbursement policies, the evolution of e-commerce, and the passage of the Health Insurance Portability and Accountability Act (HIPAA) in 1996 (Burns et al., 2002).

Burns et al. (2002) developed a more conventional value chain framework specifically for healthcare organizations (Figure 2). This framework was developed based on Porter's (1985) original organizational value chain framework (VCF) that essentially explains how organizations create and deliver value through a set of primary and support activities. The study draws on the concepts of Burns et al. (2002) value chain framework which was proposed to basically explain how healthcare organizations are creating value through their primary and secondary activities.

In the context of healthcare, however, the value chain framework redefined a reversed order in such a way that the support activities, which comprise of hospital support services; hospital diagnostic and therapeutic services; information services; and hospital administration, collectively form the foundation activities while the primary activities, which include admission; care; discharge; marketing and sales; and service constitute the front-end activities. Healthcare organizations depend on this configuration of value-chain mapping to figure out how to improve quality (or lower costs) of care by delivering or connecting patients to the services in order to fully benefit from the entire chain of activities needed for better care (Sastry, 2014).

This healthcare value chain framework (HVCF) was used as the main theoretical lens for conducting this study. Thus, the HVCF was extensively used as a guide to inform the overall design as well as data collection for this study.

3.4 ACO Enrollee Population Health Management Framework

The ACO enrollee population health management (*ACO-based PHM*) is an approach that is geared towards impacting the delivery of care to a *group of individuals* with similar healthcare needs. Kindig and Stoddard (2003) define population health as "an approach that focuses on interrelated conditions and factors that influence the health of populations over the life course, identities systematic variations in their patterns of occurrence, and applies the resulting knowledge to develop and implement policies and actions to improve the health and well-being of those populations." They went further to propose that *PHM* is concerned with both the definition of measurement of health outcomes and pattern of determinants. The determinants include medical care, public health interventions, genetics, and individual behavior, along with components of the social (e.g. income, education, employment, and culture) and physical (e.g. urban design, clean air, and water) environments.

With the current ACO-based PHM approach, healthcare organizations are shifting their focus of care by forming partnerships with stakeholders (government agencies, insurance providers, the community, etc.) with the aim of trying to proactively help minimized the risk of people falling within the high-risk patient category. The main objective behind the recent focus on population health management is because of the need to better manage and reduce healthcare costs. More specifically, and according HealthCatalyst Report, PHM helps (i) reduce the frequency of health crises and costly ED visits and hospitalizations; (ii) lower the cost per service through an integrated delivery of care team approach which includes clinicians, social workers, physical therapist and behavioral health care professionals; (iii) improve the overall patient experience, in part by providing improved access to care; and (iv) promote patient engagement and empowerment of patients to better self-manage their health and participate in the decision making process.

From 2014 Health Care Advisory Board interviews and analysis, ACO Enrollee Population Health Management Model in a form of a pyramid was developed (Figure 4). This ACO-based PHM pyramid has three hierarchical layers, with the bottom layer (*low-risk patients*) representing (i) 60%-80% of patients with minor transient conditions which can be easily managed; the middle layer (*rising-risk patients*) representing 15%-35% of patients that may have conditions not optimally managed; and topmost layer (*high-risk patients*) representing (ii) the remaining 5% of patients usually with very complex or severe diseases, conditions, or comorbidities (e.g. chronic diseases).

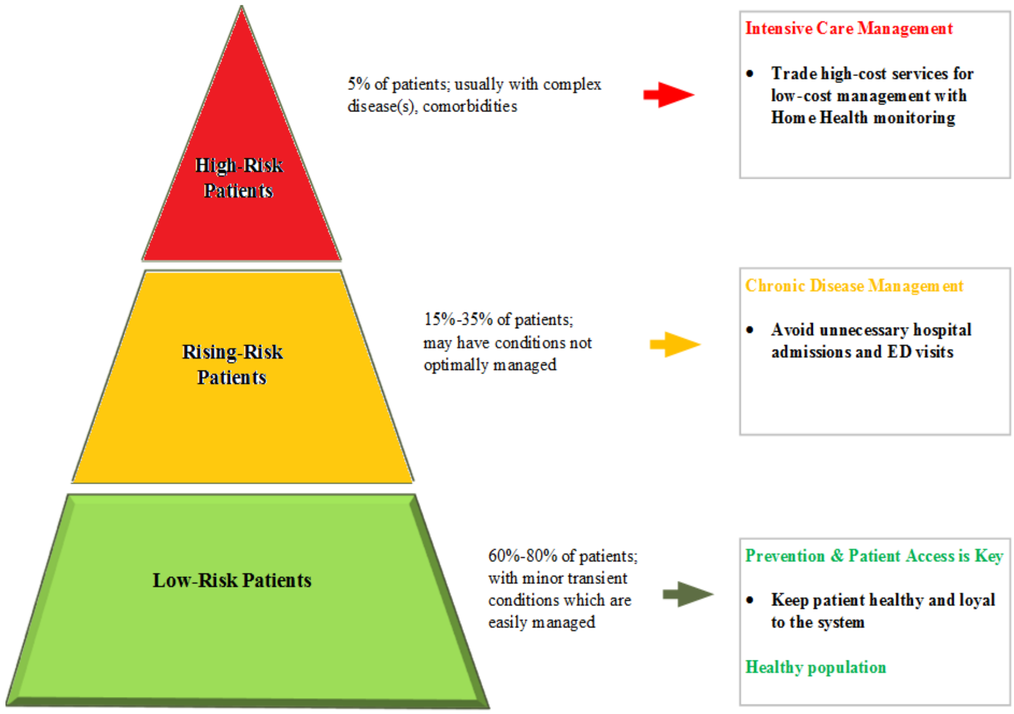

Figure 4. ACO Enrollee Population Health Management Framework. ***(Adapted from: Health Care Advisory Board Interviews & Analysis)***

People with health conditions that fall within the low-risk patients' category can be addressed through some intervention measures such as early prevention and patient access, remotely keeping patients healthy and loyal to the system in order to maintain a healthy population. However, people with health conditions that is classified as rising-risk patients can receive care through interventions such as chronic disease management in nursing facilities in order to help minimize or avoid unnecessary hospital admissions and ED visits. Lastly, patients with health conditions that falls within the high-risk patients' classification in the ACO pyramid are those brought to the intensive care unit for special care and treatment.

This study is situated in this ACO-based PHM framework by using it as a lens to understand how A&BI techniques and technologies are being leverage by a healthcare organization to manage the top 5% of high utilizers, and some of the rising risk patients.

3.5 Research Method

Following Orlikowski (1993), and Sabherwal and Robey (1993), who investigated the processes inside real organizations, this research is conducted through a case study method. Thus, I used interpretive case study approach to develop a revised HCVC framework from real organizational data by empirically examining the collective interpretations of a large healthcare organization's managers and IT employees with the aim of understanding the impact of IT and A&BI on healthcare value chain activities. I answer the research question by using an interpretive, naturalistic approach to its subject matter in which the researchers study things in their natural settings, attempting to make sense of, or interpret the phenomena in terms of the meanings people attach to them (Parveen, Jaafar and Ainin. 2015).

Interpretive case study is deemed appropriate for this research primarily because it has widely been acknowledged as a means for providing rich insight into and explanation for new and emerging phenomenon like the current adoption and use of current and emerging IT-enabled A&BI techniques (Benbasat, Goldstein & Mead 1987; Lee, 1989; Miles and Huberman, 1994; Yin, 2009). It has been noted that few IS studies utilize the interpretations of key players in the organization context (Orlikowski, 1993; Markus and Robey 1988). According to Klein and Myers (1999), "interpretative research can help IS researchers to understand human thoughts and actions in social and organizational context…" (p. 67). Domain expert employees and managers' interpretations are particularly significant, especial as managers control the way by which actions occur and provide the basis for the meaning of organizational actions (Isabella 1990; Smircich and Stubbart 1985).

Four key assumptions are critical in interpretive studies according to Isabella (1990). First, organizational members actively create their own reality. Second, the social interchange of shared experiences of organizational members creates a collective logic of the occurrence of events. Third, the interpretive literature has identified managerial views of phenomena as critical. As domain knowledge employees and managers are considered experts within their jurisdiction in the organization, their interpretations of reality have tremendous influence on the construed reality of other organizational members. Lastly, interpretative research is built on events that have already transpired, and a collective viewpoint has had time to emerge. In this study, however, I utilize interpretive case study method, which is an example of interpretive research.

In addition, I applied hermeneutic phenomenology (van Manen, 1998) as part of the method of inquiry. By adopting hermeneutic analysis to decision makers' accounts of using current & emerging IT-driven A&BI techniques in improving healthcare performance, I explored these experiences from a variety of personal, organizational, and social perspectives by reconciling vastly different views and opinions, which Merleau-Ponty (2004) refers to as arriving at the essence of the investigated phenomena to identify the common core of shared experiences. In the following section I provide detail information into the case study approach.

3.6 The Case Study

3.6.1 Theoretical Sampling and Site Selection

Similar to Oborn et al. (2011) and Lahiri and Seidmann (2012) who used a case study to investigate technology influences on doctors and organizational work flow respectively, I identified a large healthcare organization with five affiliate organizations to investigate the organizations' personal experience in IT-enabled A&BI, making decisions, creating value with IT for their organizations. This healthcare organization is deemed appropriate to be used as the case subject because not only is it currently growing and expanding its IT operations but also because management expressed great interest in investing significantly to elevate the current IT-enabled A&BI capabilities to industry standard. In addition, management want to know how their current state of IT-enabled A&BI capabilities and applications compare with other leading healthcare organizations in providing value added patient-centric care. In this regards, top management of the organization were very cooperative and supportive in providing all the necessary support in terms of data collection and other necessary logistics needed to ensure that the research is successfully carried out.

The Healthcare Organization (HCO) is one of the largest care providing organizations (ranks among the top 2% best "High Performing" care systems in US) located in the South-Eastern part of the U.S. This HCO is a non-for-profit health care network serving people living in five major counties with the primary objective of providing excellent and quality care for its patients. With its high commitment to excellence which is shared by more than 11,000 employees, 1,300 physicians, and 1,200 volunteers, the HCO is regarded as one of the region's largest and most comprehensive healthcare networks comprising of six major hospitals or medical centers. The hospital within this larger healthcare system that is currently participating in this study saw about 25,395 discharges and 106,662 emergency department visits according to the 2016 Fiscal Year record. In addition to its size, this HCO also boasts of rising revenue as more outpatient services are being delivered and its operating surplus is back on the rise too. In total, the HCO reported an operating surplus of $33.4 million on revenue $1.4 billion for the 2015 Fiscal Year.

3.6.2 Unit of Analysis

While the unit of analysis for this research is the organization, data was collected from a total of 30 IT employees and other top-level managers (see Table 5). Hence, the unit of analysis is aggregate perspectives of employees' and managers' experience with the influence of diverse IT and A&BI systems use on their organization. As the research endeavor took place within one large organization, it was expected that each IT-enabled task would be carried out within inherent procedural similarities and organizational philosophies. Participants interviewed come from varying education and qualification background. I asked unique questions related to the role of the study participants within the organization. For example, participants were asked to provide exemplar use cases of how they apply IT-enabled A&B systems, tools and techniques; the challenges they faced; and benefits they have gained.

Different tasks or use cases successfully executed through IT were explained by the 30 different IT employees and managers interviewed and their interpretations were recorded on audio recording machine and paper for further analysis. In addition to the interview, company documents and other secondary sources such as articles, news publications, company's annual reports, etc. were also examined. This triangulation across multiple IT employees and managers, as well as other secondary sources provide manifold perspectives of the research objective in addition to the in-depth validation of the underlying concept (Corbin and Strauss 2008, Orlikowski 1993).

3.6.3 Data Collection and Analysis

This study used open-ended semi-structured interview techniques with probes (Rossi, Wright, and Anderson 1983) to collect primary data from a total of 30 IT staff and managers in a large healthcare organization. Interview data was collected over 8 months' period (i.e. May 2016 – January 2017). Interviewees come from diverse education background with rich IT-related work experience (Table 5). The idea of using multiple informants from variety of functional backgrounds and levels originated from Phillips (1981), who strongly argued that multiple informants are more reliable sources of data collection than just a single one.

Job titles or position held by participants include: Chief Medical Officer (*R1*), Chief Medical Information Officer (*R2*), Chief Data and Analytics Officer (*R3*), Executive Director of Healthcare Analytics (*R4*), Director of Clinical Business Intelligence (*R5*),…, etc. Participants were randomly assigned pseudonyms, *R1,…., R30*, (see Table 5) in order to protect their identity based on initial data masking agreement.

Table 5. Interviewees Background Information

#	Informant	Job Title/Position	Education Level	Years of IT-related Work Experience
1	*R1*	Chief Medical Officer	Ph.D., MD	8
2	*R2*	Chief Medical Information Officer (CMIO)	MD	15
3	*R3*	Chief Data and Analytics Officer	MBA	25
4	*R4*	Executive Director of Healthcare Analytics	MSc in Nursing & Certificate in Business	16
5	*R5*	Director of Clinical Business Intelligence	BSc. in IT	24
6	*R6*	Director of Meaningful Use	MBA, RHIA	40
7	*R7*	Health Information Analyst	BSc. in IT	12
8	*R8*	Instructional Designer (Epic Operations)	MSc. in IT	12
9	*R9*	Health Information Mgt./Identity Instructional Designer	MSc. Health Administration	10
10	*R10*	Manager of BI Systems	MSc. in IT	10
11	*R11*	Systems Analyst III	MBA	28
12	*R12*	Business Intelligence (BI) Application Analyst	BSc. Engineering	12
13	*R13*	BI Application Systems Developer and Analyst	BSc. Computer Science	7
14	*R14*	BI Report Developer	Ph.D. in IT	5
15	*R15*	BI Developer	MSc. in IT	12
16	*R16*	BI Report Developer	BSc. Business Administration	5

17	*R17*	Reporting Analyst	BSc. Computer Science	15
18	*R18*	Data Architect	Master’s in IT	14
19	*R19*	Systems Analyst II	BSc. Computer Science	8
20	*R20*	Database Analyst Logical	BSc.	15
21	*R21*	Technical Analyst	BSc. Computer Information Systems	15
22	*R22*	BI Report Developer	MSc. Health Administration, Registered Nurse (RN)	12
23	*R23*	ETL Developer	BSc. Computer Science	12
24	*R24*	Director of Epic Operations & Training	MSc. in IT	10
25	*R25*	Manager, Quality Performance and Clinical Informatics	Master of Science in Nursing, (MSN)	14
26	*R26*	Chief Administrative Officer	MBA	20
27	*R27*	Reporting Analyst, Clinical Business Intelligence	MSc in IT	10
28	*R28*	Director, Physicians/Clinical Services	MD	20
29	*R29*	Application Analyst, Clinical Informatics	MSc in IT	12
30	*R30*	Application Analyst	BSC in Business Admin.	14

Interview participants were identified through peer and management nomination. Abdolmohammadi and Shanteau (1992) have shown that professionals in a field are competent to identify a consistent set of attributes they associate with experts. Therefore, nomination rather than factors such as job titles and education level was used in identifying respondents.

I used open-ended interview techniques with probes (Rossi et al. 1983). An interview protocol was used as a guide to facilitate the process. This protocol was loosely developed from the available general frameworks of expertise, but was designed to elicit and probe concepts mentioned by interviewees. Respondents were asked to provide exemplar cases where IT or A&BI used has caused a paradigm shift in the way they execute certain tasks. For example, “When one mentions the word A&BI technology from healthcare context, what characteristics does this make you think of?”

Based on the response to the questions, probing questions were asked to elicit further specific attributes. The interviewers did not constrain responses to questions (Payne 1951). Each interview lasted between 30-60 minutes. The interviews were transcribed to a document format, ranging from 6-12 pages. Table 6 below provides descriptive statistics of respondents in this study.

Table 6. Descriptive Statistics of Respondents

	Number of people interviewed = 30	
	Mean	**Standard Deviation**
Experience in doing or managing IT related work (number of years)	14.63	7.43
Age (number of years)	45.90	11.17
<u>Education</u> • Undergraduate degree (%) • Graduate degree (%) • Post graduate degree (%)	 36.67 50.00 13.33	 ---- ---- ----

Once each interview session was completed, field notes were typed and audio recordings transcribed into word document using a software called “Transcribe”. Transcriptions were independently carried out by researcher and an associate, compared and contrasted, and eventually consolidated into one final document. Each final consolidated transcription was then sent back to the respective informant for content validation. Majority of the informants confirmed that the transcriptions were true reflection of exactly what they said and that, there were no errors or mistakes in the transcript document that they have reviewed. However, about 2-3 informants identified a few minor mistakes in the transcripts and they played instrumental role by providing guidance and directions to help correct the anomalies. After the transcription, the process of unitizing and categorizing was carried out in a qualitative data analysis software (Atlas.ti and R Qualitative Data Analysis [RQDA]) program which helped make more sense of the data. Unitizing is the coding operation in which information is isolated from the text (Glaser and Strauss 1967; Parveen et al. 2015). I used axial coding method to help tease out emerging themes for various sections that were identified from the transcripts. The words, phrases, etc. were then coded based on common themes that have been agreed on prior to the analysis (Stake 1994).

I used four methodological data-analysis steps interwoven into the cycles of the hermeneutic circle as adapted from van Kaam (1966) and Moustakas (1994); epoché, phenomenological reduction, imaginative variation, and synthesis. In the first step, epoché, I identified and set aside any personal biases and pre-judgment for each hermeneutic cycle. For the second step, *phenomenological reduction,* I prepared a textual description of each interview. I used the resulting narratives, which comprised of about 5000 statements, to recognize and identify the discussed issues, the participants' viewpoints, and the meaning of individually experienced phenomenon (Moustakas, 1994).

I analyzed the narrative statements and assigned each one a number of codes to represent and classify their content. Using the open-coding process (Glaser and Strauss, 1967), I identified the aspects of IT-enabled A&BI use in the organizations that had some importance to study participants. I subsequently reviewed the preliminary codes (see Appendix B) and combined those with similar meaning in a context relevant to this study. I consequently refined the coding system to comprise only 25 codes, which I applied to all narrative statements, to identify those aspects of IT-enabled A&BI that, from the perspective of the study participants, had some relevance to and significance for organizational value creation.

In the third phase, *imaginative variation*, I determined the structure of the phenomena and their meaning. In this process, I explored the previously identified themes by varying the participants' perspectives and adopting different frames of reference to look for overlaps, confirmation, complementarity, and conflict in the views that the participants held. Lastly, in the final step of the hermeneutic phenomenological process, *synthesis*, I identified the essence of the study participants' shared experience. I further compared and contrasted such shared views with the extant literature on IT-enabled A&BI applications in healthcare organizations and performance improvement.

3.6.4 Validation Process

In this section, I present a summary of validation criteria that I used for evaluating the entire research approach. Table 7 lists how the evaluation criteria were met.

Table 7. Evaluation Measures Applied to this Methodology

#	Methodological Issue	Validation Criteria	Results of this Study
1	**Research Focus**: Example: what are the objectives of the research?	To identify the extent of impact of IT-enabled A&BI on healthcare value chain and develop a revised HCVC framework if necessary.	Demonstration of the need to update the current HVCF and systematically developing a revised framework that is more reflective of current healthcare value creation and delivery process.
2	**Choice of Source**: Example: how do we capture relevant knowledge?	Elicitation sample (Experts) Site selection	• Study carried out in a large healthcare organization with five affiliate organizations and relatively large number of experts in sites. • Experts nominated by superiors and peers (Abdolmohammadi 1992) • Limitation: Convenience sample.
3	**Sampling Strategy:** Example: Does the choice of sample reflect research objectives?	Diversity of context to fully capture the phenomenon	Sites selected in context based on knowledge of diverse IT-related job types

4	**Construction of Concept Maps:** i. Categories: Are the categories conceptually relevant? ii. How do we capture the concepts in a meaningful manner?	• Identification of all relevantly related statements from respondents • Interpretation of findings through available literature appropriate for the research topic	• All important statements were pulled from transcripts. • Organization of relevant statements into concepts, categories and constructs by multiple raters and software.
5	**Unit of Analysis:** Example: Is the level of analysis consistent with the phenomenon under investigation?	Level of aggregation used in this study.	This study sought to understand the impact of HIT on healthcare value chain, hence, concept level aggregation of expert respondents is appropriate.
6	**Convergence:** Example: Is the knowledge structured or random?	Evaluation of sample size and frequency that concepts are revealed	• Point of redundancy calculation
7	**Validity of Findings:** Example: Do findings make sense?	Relevance to tacit understanding of respondents and knowledge of general theories	• Member checks performed • Comparisons made to existing literature.

In the following section, I present the general findings from this study with extensive discussion about the main outcome the study came up with which is a revised healthcare value chain framework.

3.7 Findings and Discussion

The in-depth knowledge gained after identifying the themes in phenomenological reduction phase helped in exposing the structure of meaning hidden in the stories that participants shared during the interviews. To expatiate the connection between IT-enabled A&BI capabilities and healthcare organization value chain, I illustrate the properties with statements of personal experience from the study participants and compare their statements with concepts drawn from the literature. I describe the overall findings in the following sections.

3.7.1 Evidence for the Need of a Revised and Updated HCVC Framework

When interview participants were presented with the healthcare value chain framework (HCVCF) and asked to share their opinion about the framework's relevance and applicability with regards to the current healthcare organizations' general practices, majority of respondents remarked that the framework is outdated and therefore needed major revision. Thus, about 27/30 (representing 90%) of participants strongly recommended a revised version of the HCVC framework because the current framework was regarded as being too outdated and as such, it does not sufficiently represent current healthcare practices.

Upon thoroughly analyzing the interviewees experience with current healthcare administration and practices, it became more apparent that the Burns et al. (2002) HCVC framework indeed needed major revision. For example, the Chief Medical Officer, the Chief Medical Informatics Officer, the Executive Director of Healthcare Analytics, the Director of Meaningful Use, etc. all came to the same conclusion that a newer version of the HCVC framework that reflects current healthcare practices would be more useful to healthcare organizations. They went further to describe the current system of the healthcare value chain as being more focused on the *ACO-based population health management (PHM)*.

Below are selected excerpts from the interview responses that suggest the need to revise the HCVC framework:

> All healthcare organizations are trying to do is more preventive and more relationship building with the patient, I don't see where that is covered in your primary activities of the HCVC framework. (R15, BI Developer)

> It's a little confusing to me...... everything under the supporting activities.... like how does one know what supporting the primary activities. (R13, BI Systems Developer & Analyst)

Respondent (R13) went on to say….,

> Personally, I think the framework needs to be updated. This is reactive from back in the day, we are moving more to go proactive, identifying risk factors for patients coming in to the ER for whatever and they came in multiple times for these three different reasons. This is leading up to the bigger issue that they are going to be admitted for possible death where it starts at re-admission and move forward. We are reaching out to them before the admission now. We are coming in just to see their Primary Care, we are doing a lot more than what we are used to, and also, with how we get paid now - we get paid fee-for-service now. In the past, we wanted you to come in and get sick and we'll pay but now we are getting paid to keep you out of the hospital. So, I would say the HCVC framework you have is dated. (R13, BI Systems Developer & Analyst)

Another respondent (R19) was also quick to remark:

> As far as primary activities from what I'm seeing on this framework are concerned, yeah, I would say discharge and admissions probably should be wrapped into one kind of area. I mean, to me discharge and admissions are kind of little fuzzy and I can't read the care part that goes underneath the same scenario. The admissions and that part of the whole care atmosphere that we currently have here at my organization is that being discharged and sent home for observations is where we are currently heading towards.

> So, to me, those three areas (admissions, care, discharge) must be merged because they are kind of grey areas because the data kind of merges a lot in these areas. (R19, Systems Analyst II)

Based on these revelations, it becomes apparently necessary that the HCVC framework is indeed revised in a way that is geared towards the current accountable care organizations (ACO) approach or system of care giving which every healthcare organization is currently moving towards. It was learned from the interviews that healthcare organizations are now shifting towards the ACO approach to care management by forming partnership with all stakeholders to ensure that the masses of the population stay healthy and minimize the risk of being severely sick.

> We have moved away from this kind of hospital admission in the traditional hospital care type thing into a process that basically aims at how can we keep people healthy and out of the hospital in the most cost effective way. (R3, Chief Data & Analytics Officer)

In view of this, the call for a revised version of the framework that currently captures healthcare organizational practices and needs is appropriate and timely. Consequently, I propose a revised HCVC framework (see Figure. 3) using inputs from interviewees' responses as expressed in the following excerpts:

> I think… I mean I would change the order. I really think, that we are just talking about the primary activities, the marketing and sales is probably the most important. You want people to come and have their.... marketing and sales because you have their name out there, you want your brand out there, you want people to look their first.
>
> And then your services because you need to have all what they are looking for, and you need to be good at what they are looking for. And then once they decide they want the service, then I think your care comes in. How does the

> service..., how to rate it after...., did they have a good experience…? did they have a good outcome? All that. And then, if they had to be admitted, then your admission and your discharge goes together.
>
> These days it's like in the form of a circle... it's not like a layout as you see... it goes back and forth like a wheel. You start from service, we want people to be away, and providing care to them at their home, it costs the hospitals when there are more admissions, kind of like.... the hospital is trying to avoid penalty and all that. So they try to be more focused on the low-risk people within the community. They want to keep everybody healthy. (R22, BI Report Developer)

3.7.2 The Revised Healthcare Value Chain Framework

The revised HCVF is presented in Figure 5. This framework describes a process that comprise of two major distinct categories: primary activities and support activities, with the primary activities having two subcategories: clinical care giving services and non-clinical care giving services. Furthermore, the nature of the framework and the relationships between the concepts and categories suggest that the current healthcare process is cyclical, with population or consumer wellness being the core objective around which is a feedback loop among different categories within the framework. Figure 5 below is a schematic diagram of the revised HCVC framework supplemented by explanation of the different layers, categories and concepts in Table 8.

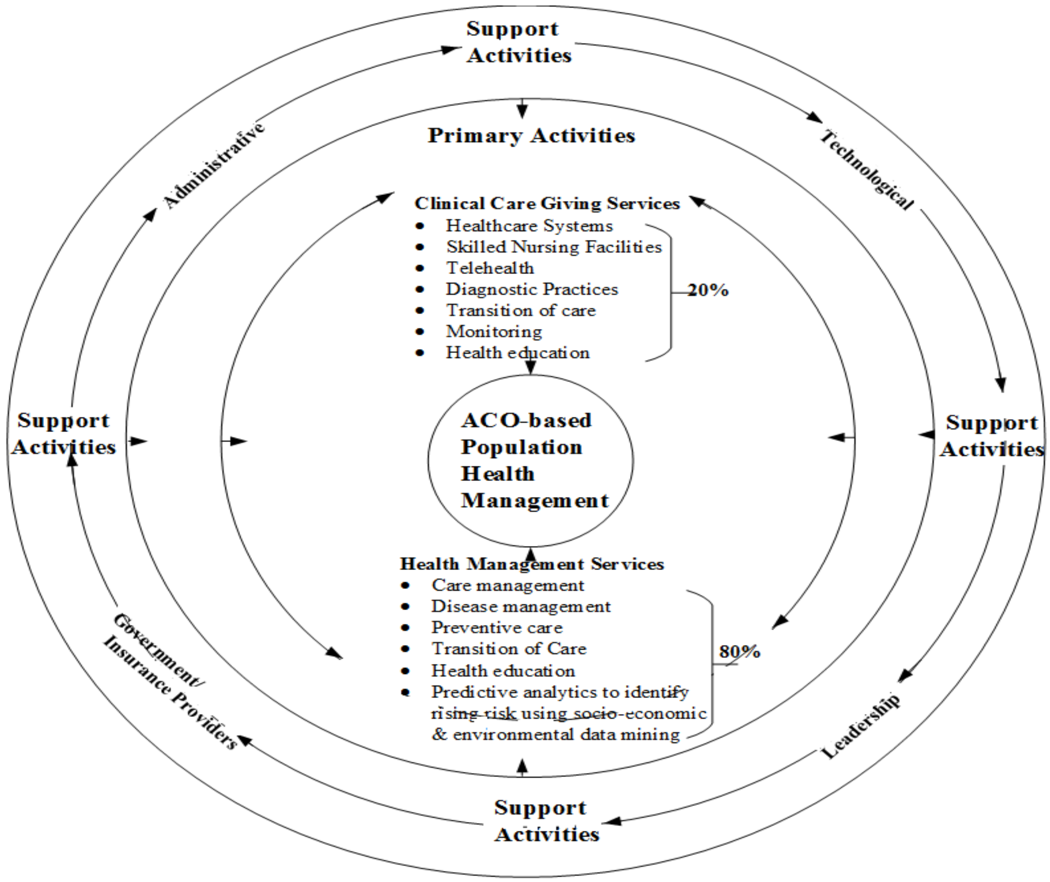

Figure 5. IT-Enabled Healthcare Value Chain Framework for Population Health

3.7.3 ACO-based Population Health Management Layer

The revised HCVC framework above shows how healthcare value creation and delivery process has significantly been transformed and still reforming into being more consumer/population health-centric. In other words, the focus of current healthcare providing organizations is to keep the general population healthy remotely by using IT to monitor consumer behavior as well as influence their decisions that have consequences on their health. In the center (core) of the revised framework above is the core objective of the current healthcare industry which is basically to ensure that majority of the population or consumers stay healthy in their communities. This is amplified by the following excerpt from the interview:

> We have moved away from this kind of hospital admission in the traditional hospital care type thing into a process that basically aims at how can we keep people healthy and out of the hospital in the most cost effective way. (R3, Chief Data & Analytics Officer).

3.7.4 Primary Activities Layer

Next to the core (nucleus) is the primary activities that healthcare organizations provide. The primary activities, according to interview responses, comprise of two main tasks or services: 1) clinical care giving and 2) health management services. The clinical activities are the conventional caregiving activities that healthcare organizations provide to their patients within the hospital or care delivery environment. This includes services such as admissions into the hospital facilities, diagnostic of diseases, treatment, transition of care, skilled nursing care facilities etc. Healthcare providers are now targeting to minimize percentage of the population that receive care and other services within the hospital facilities to not more than 20%.

> We (i.e. our organization) try as much as possible to meet current industry standard of care delivery and value creation. As such, we try to engage majority of the people in the communities by remotely reaching out to them through social media, blocs, emails, etc. with wellness keeping advices and other interventions to help them stay healthy so they don't have to come to the hospital because they are sick. This way, we are able to offer better treatment services to not more than 20% of people who are seriously sick and need our utmost attention. (R6, Director of Meaningful Use)

The other service provided within the primary activities is the health management services (HMS) which healthcare organizations are now trying to achieve through high investment in IT. HMS involves managing the health of the remaining 80% ACO enrollees, who belong to the low-risk category of the population, through collaborative effort of clinicians, IT, care coordinators, and business analysts to proactively engage and work with their patients in order to help minimize the risk of them falling into the high-risk patient category. HMS-based activities include medical care, public health interventions, genetics, and individual behavior, along with components of the social (i.e. income, education, employment, and culture) and physical (e.g. urban design, clean air, and water) environment.

With ACO-based HMS, healthcare organizations are also attempting to encourage the healthy population to frequently indulge in exercises, constantly reminding them to be conscious about their living environment, and encourage the pursuit of higher education in order to be able to get high earning jobs that will help provide for their basic needs.

3.7.5 Support Activities Layer

The support activities layer is the outermost layer in the proposed healthcare value chain framework which healthcare providers also deem very important in creating and delivering value to consumers. As can be seen in the revised framework, the arrows pointing from each of the layers towards the inner core (nucleus) of the framework symbolizes either direct or indirect influences of each layer on value creation and delivery process towards the inner population (nucleus). For example, through extensive use of IT, healthcare organizations are targeting to remotely deliver valuable care and other health services to the majority of the population (80%) by partnering with them and other stakeholders (government agencies, insurance providers, etc.) to help them make informed decisions about their health.

> … and I think we talked about it, what you know if our goal is healthy community then we support people in their daily lives for the eighty to ninety percent of the time that they are not engaged with us right and how do we do that and of course how do we do all these other things like you mentioned for the 10-20% of the time when you are engaged. (R24, Director of Epic Operations & Training)

Other support activities that also impact value creation and delivery include leadership and administrative support/commitment, government and insurance providers' policies and agreements, etc. Respondent (R3) alluded to specific example of the support activities as captured in the following excerpt:

> The only thing I was thinking about and you sort of hit on it right is apparently you have the discussion about the transformation towards let's keep you healthy and there is a lot that have to transform in the healthcare system to support that particularly reimbursement because there is no incentive for Physicians to do that other than altruistic incentives right now. (R3, Chief Data & Analytics Officer)

In summary, unlike the old HCVC framework (see Figure 2) originally proposed by Burns et al. (2002), the current proposed HCVC framework differs in many ways. One major change that majority of the interview respondents pointed out is about the cyclical nature with feedback loop process of the current healthcare practice. For example, about 90% of the respondents consented to the fact that, unlike the old framework that is apparently linear and hierarchical, the current system of healthcare rather operates in an eco-system comprising of several different interacting factors that influences population health. Based on these revelations, it becomes important that the current framework is represented in a cyclical nature to emphasize the fact that peoples' health are influenced by so many factors around them. This has resulted in a revised HCVC framework that depicts how healthcare organizations are currently creating value for patients (clients) and deriving value from them in return. In Table 8 below is a summary of specific activities that are carried out in each of the various domains of the revised HCVC framework.

Table 8. Revised IT-Enabled Healthcare Value Chain

<table>
<tr><td rowspan="2">Primary Activities</td><td>Clinical Care Giving Services</td><td colspan="4">Examples include:
Healthcare systems, skilled nursing facilities, telehealth, diagnostic practices, transition of care, monitoring systems, and health education</td></tr>
<tr><td>Health Management Services</td><td colspan="4">Examples include:
Care management, disease management, preventive care, transitions of care, health education, predictive analytics identify rising risk using socio-economic and environmental data mining techniques</td></tr>
<tr><td colspan="2">Support Activities</td><td>Technological support
• IT infrastructure
• Software
• IT enabled process/techniques</td><td>Administrative Support
• Strategic planning
• Effective management and use of resources</td><td>Leadership Support
• Leadership style
• Strategic alignment of clinical and business activities</td><td>Government and Insurance Providers
• Policies
• Standards
• Regulations</td></tr>
</table>

3.7.6 Clinical Care Giving Indicators

Due to the complexity of healthcare, and the myriad factors that impact quality and performance, it is impossible for a single metric or indicator to reflect accurately changes to the systems. For example, efficiently functioning HCOs must measure many aspects of their systems and procedures including healthcare systems activities, skilled nursing facilities, telehealth, diagnostic practices, transition of care, monitoring systems, health education, etc. I explain each of these components in the following section.

- **Healthcare systems**: is the organization of people, institutions, and resources that deliver healthcare services to meet the health needs of target population. Health systems include not only the institutional or supply side of the health system, but also the population' health or wellbeing.

- **Skilled nursing facilities (SNFs)**: are nursing facilities that are equipped with highly skilled nurses who provide quality treatment and services. Patients in SNFs are generally shorter stay patients who are receiving continued acute medical care and rehabilitative services. While their care may be coordinated during their time in the SNFs, they are then transitioned back to the community. Patients in SNFs often require more frequent practitioner visits – usually from 1 to 3 times a week. In contrast, patients in ordinary nursing facilities (NFs) are almost always permanent residents and generally receive their primary care services in the facility for the duration of their life.

- **Telehealth services**: is the use of remote communication or monitoring mechanisms (e.g. telephones) for care coordination such as timely communication of test results, timely exchange of clinical information to patients. For rural or remote patient, patients are managed using remote monitoring or telehealth options that involve systematic and coordinated care, incorporating comprehensive patient education, systematic testing, tracking, follow-up, and patient communication of results and dosing decisions.

- **Diagnostic practices:** is the ability of HCOs to provide the best possible care at the right time by using the right techniques and procedures to detect and treat diseases to the right patients in the most efficient and safe manner possible.
- **Transition of care:** is the situation in which a patient is transitioned or referred from one care facility to another setting of care or healthcare provider for better treatment and care.
- **Monitoring:** is the time period of care giving during which healthcare providers assess if allowing for extended time requirements may enhance the value associated with generating more effective outcomes, or conversely, the extended time, may reveal that more time has little or no value added for activities when associated with desired outcomes. Monitoring health conditions of individuals to provide timely health care interventions or participation is the ultimate goal of population health management.
- **Health education:** is any combination of learning experiences designed to health individuals and communities to improve their health by increasing their knowledge or influencing their attitudes.

3.7.7 Health Management Services (HMS)

The higher costs of care in the U.S. are not producing better outcomes. Research shows that of the countries covered in the 2015 Commonwealth Fund Study, the U.S. had the lowest life expectancy at birth – 78.8 years, and it also performed poorly relatively for chronic conditions such as diabetes (third-highest rate for lower extremity amputations as a result of diabetes) and ischemic heart disease (highest mortality rate).

All these findings confirm that the current encounter-based medicine practiced most commonly today is not working for the population health. As a result, the current U.S. healthcare systems need to adapt by learning from public health programs and apply those lessons when managing chronic conditions across populations.

It has been shown that about 80% of what affects health outcomes is associated with factors outside the traditional boundaries of health delivery as depicted in Robert Wood Johnson's Collaborative Model (Figure 6). These factors include health behaviors (e.g. tobacco use, sexual activity, etc.), social and economic factors (e.g. employment, education, income, etc.), and physical environment (e.g. air quality, water quality, etc.). When healthcare delivery systems expand their interactions with people in these territories, now purview of the public health system, outcomes are expected to improve.

True population health management, according to Robert Wood Johnson Foundation (2014) model, requires a collaborative strategy between leaders in healthcare, politics, charity, education, and business. This implies that policies and programs within the physical environment as well as socio-economic factors influence individual health factors which, in turn, influence their health outcomes. And of these health factors, only

20% can be attributed to clinical care, the remaining 80% are attributed to external factors (e.g. physical and socio-economic factors) and behavioral factors. Based on this revelation, healthcare providers and other stakeholders are resorting to the use of technology-based resources including A&BI techniques (e.g. data mining) to help minimize the influences of these external factors on the health of population.

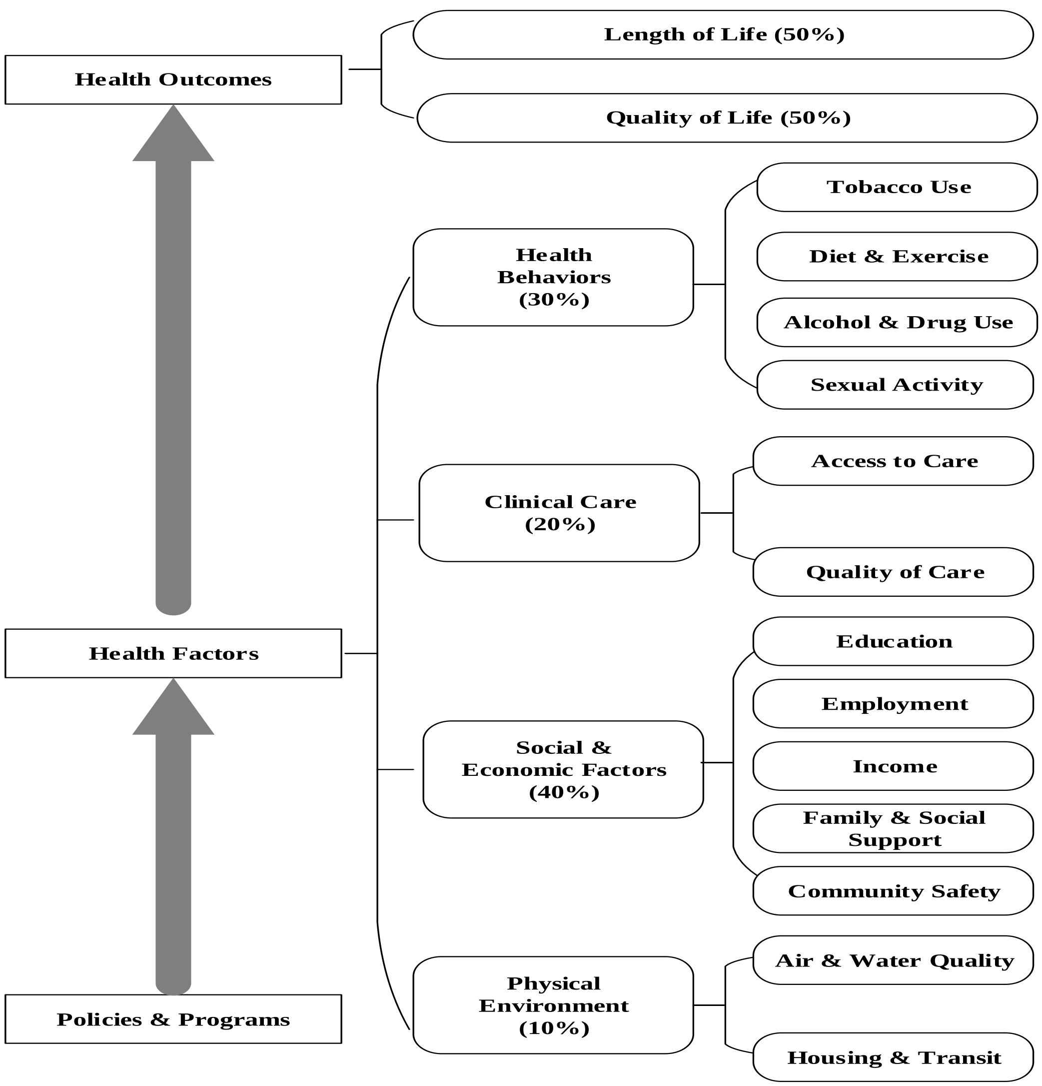

Figure 6. True Population Health Management Model. (Adapted from Robert W. Johnson Foundation, 2014)

3.7.8 Support Activities

These are activities such as technological support, administrative support, leadership support, and other stakeholder support, that help drive high quality of care delivery within HCOs. Each of these activities are explained in details in the following section.

- **Technological support:** this comprise of IT infrastructure (e.g. hardware, software) and IT-enabled process and techniques that HCOs heavily rely on to provide better care quality. Due to the new ACO Act regulations, HCOs are now increasing their investment in technological solutions to better manage business operations and treat patients. Ideally, the analytical needs of HCOs and the technological requirements to supply those needs highly depend on the organization's IT infrastructure deployment strategy.
- **Administrative/Leadership support**: this encompasses effective administrative and leadership strategic planning, effective management and strategic use of resources, and strategic alignment of clinical and business activities that HCOs implement in order to provide quality of care and services.
- **Governmental and other stakeholder support**: government and other stakeholders such as insurance providers also provide support to HCOs in a form of incentives (such as the HITECH Act and Meaningful Use requirements) with the aim of motivating them to provide better quality of care and services. In addition, these stakeholders influence the quality of individual and population health with their policies, standards, and regulatory compliance that they impose on HCOs.

While each of these domains is equally important and warrants further research investigation to help HCOs improve the quality of service they provide, this study only focuses on the *technological support activity* domain as it is one of the key interests of HCOs. Thus, I highlight the various IT applications in relations to analytics and business intelligence (A&BI) technologies, techniques and process that are currently being deployed within each of the various domains of the HCVC framework. Therefore, in the following section I present examples of such IT-driven A&BI systems that are being leveraged to improve performance.

3.7.9 Application of IT-enabled A&BI Tools and Techniques in the Revised HCVC Framework

To answer the main research questions guiding this study, the revised HCVC framework was sent back and shown to the interviewees of the same case organization. The reason is to have them confirm the validity of the revised HCVC framework, and also provide their knowledge or perspectives about the use of various IT-enabled A&BI systems, techniques and processes that are currently being applied in each domain of the revised HCVC framework. About 95% of respondents unanimously consented to the revised HCVC framework as being a true reflection of how value creation and delivery to patients and to their organization is being channeled by the current ACO care giving standards.

Based on the follow-up case study data, supplemented by in-depth content analysis of the extant literature, I found that healthcare organizations are currently expanding their investments in new and emerging IT-enabled A&BI systems, processes and techniques. Respondents provided broad varieties of IT-enabled A&BI systems and tools currently being implemented in healthcare organizations as revealed in the following excerpt:

> analytics and business intelligence is definitely growing in our organization and currently there are a few of the technologies we look into – some of them are being implemented and some of them are being planned. For data screening, we use the traditional systems such as Excel, SAS, and Minitab. However, due to the rapid growth in volumes of data that we have, we have decided to go into EPIC integrated systems where we are able query massive data and extract reports. Moreover, we are also currently exploring the possibilities of implementing big data systems such as Hadoop Ecosystems. (R1, Chief Medical Officer)
>
> We are currently growing and as such, we have been exploring all the open sources that is available in the market which can be leveraged to perform better analytics. In that regards we look into analytics and visualization tools like QlickView. We want to be able to use it for certain types of analytics but we found Hadoop as being a very strong tool. (R12, BI Application Analyst)
>
> So we have a big strategy which we call a data-driven strategy. Our strategy is to become data-driven Healthcare Organization. The foundation of that which is the Enterprise data warehouse (EDW) will be used to bring together and integrate data from some of our major systems obviously EPIC which is the major EMR system. We have another major system called Lawson which is another ERP system that will be all the financial data. So we bring together the Clinical, Financial data, the data associated with our ACO Triad Health Network (THN). We'll integrate all that information in the data warehouse so that will become the foundation. And then the BI Team along with the analytics team will develop applications and reports and whatever we need out of the Enterprise data warehouse that service not only the clinical care perspective but also the operational, financial perspective as well.
>
> So we use right now mainly two technologies - we use the Microsoft BI stack that here we refer to it as Power BI. So we use that and then we use QlikTech or QlikView to render visualizations of dashboards and reports from the data warehouse. We will eventually bring in Tableau which will be another one and then part of our bold vision with the analytics troop is to have data scientist and advanced data analytics for predictability and things like that so we will probably bring in Python and R and few other tools so that we can do some of that modeling. (R5, Director of Clinical BI)

In addition to these A&BI systems, tools and techniques revealed from the case study, I also identified extra A&BI systems, tools and techniques in the literature that either confirms or compliments the findings from the case study. I then mapped these A&BI systems, tools and techniques into their most frequently applied corresponding areas in the revised HCVC framework as depicted in Figure 7 and Table 9 respectively below.

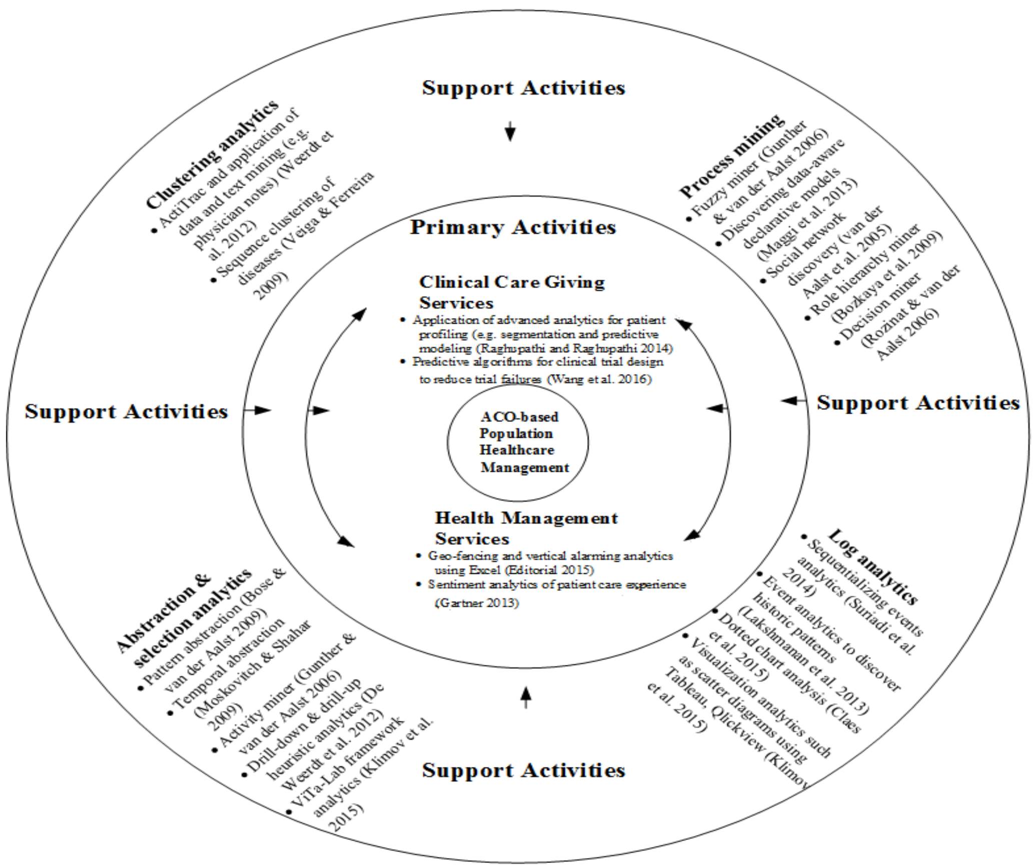

Figure 7. Sample Use Cases of A&BI Systems, Tools and Techniques within the Revised HCVC Framework

As shown in Figure 7 above, it can be inferred that healthcare organizations are heavily investing in current and emerging IT-enabled A&BI systems, tools and techniques in their support activity domain of their value chain network than they are in the primary activity domain of the network. Example of IT-enabled A&BI techniques currently being used or explored to create value include clustering analytics on disease types or patient population using different techniques such as hierarchical clustering, k-means clustering, etc. Process mining analytics to analyze and study patients' claims data using fuzzy logic or neural network technique is another technique being used in the support activity domain of the value chain. Additionally, analysis of log data which involves sequentializing of events analytics to discover historic patterns from data using visualizing tools such as Tableau and Qlikview is also becoming common. Finally, abstraction and selection analytics such as pattern abstraction, temporal abstraction, activity mining of treatments and their effects on patients are other IT-enabled A&BI techniques that are becoming prevalent in the primary activity domain of the value chain network of healthcare organizations

Contrarily, investment in A&BI is minimal in the primary activities of their value chain network as very few techniques were discovered in this domain of the value chain network of healthcare organizations. For the clinical care giving category of primary activity domain, it was discovered that predictive analytics techniques using predictive algorithms and clinical trial experiment to disease diagnostics and treatment is most rampant techniques. On the other hand, I found that healthcare organizations have begun exploring prescriptive analytics techniques that utilizes social media or unstructured data about patients' behavior within their social and natural environment. These analytics techniques, such as sentiment analysis, enables management of healthcare organizations to remotely monitor patients and indirectly influence their decisions by prescribing healthy living activities such as regular exercises, eating healthy, etc. Table 9 below is a summary of analytics systems, tools and techniques currently being used to drive value creation and delivery.

Table 9. Example of A&BI Applications in Revised Healthcare Value Chain

Primary Activities	**Clinical Care Giving Services**	• ***Healthcare systems***: application of advanced analytics techniques (e.g. segmentation and predictive modeling) to proactively identify preventive care beneficiaries (Raghupathi & Raghupathi 2014) • ***Skilled nursing facilities***: clustering analysis to decongest ER facility; interactive visualization of care giving processes (Chen et al. 2012) • ***Telehealth***: device or remote monitoring applications to capture and analyze near real-time patients' behavior and reactions to treatments or test trials (Health Catalyst 2012) • ***Diagnostic practices***: predictive algorithms for clinical trial designed to reduce trial failures (Wang et al. 2016 • ***Transition of care***: analyzing disease patterns and tracking disease outbreaks through public health surveillance and speed response optimization mechanisms. This helps facilitate patient adjustment processes to new care environment (Raghupathi & Raghupathi 2014) • ***Monitoring systems***: using A&BI tools such as Tableau and Qlickview to monitor adherence to drug and treatment regimens, and detect trends that lead to individual and population wellness (IBM 2013; Zenger 2012) • ***Health education***: network analysis techniques to help create awareness disseminate healthy lifestyle habit. Patient behavior and sentiment analytics to describe and predict patient activities and preference (Gartner 2013).

	Health Management Services	**Social activities** • Sentiment analysis of patient care experience • Patience profile analytics using predictive modeling to identify vulnerable locations for disease contamination	**Physical activities** • Physical services improvement through optimal practice management using relative value unit (RVU) analytics (Gartner 2013)	**Environmental effects** • Geo-fencing and vertical alarming analytics using Excel (Editorial 2015) • Event analytics to discover historic patterns (Lakshmanan et al. 2013).	**Economic influences** • Clinical operations analytics to identify more clinically relevant and cost-effective ways to diagnose and provide treatment to patients (Raghupathi & Raghupathi 2014)

	Technological support	**Administrative Support**	**Leadership Support**	**Other Stakeholders (e.g. gov.)**
Support Activities	• ActiTrac & application of data and text mining on documents such as physician notes (De Weerdt et al. 2012) • Visualization analytics such as cluster diagrams using Tableu, Qlickview (Klimov et al. 2015) • Dotted chart analysis: a fast tool for visualizing the spread of an event such as contagious diseases (Claes et al. 2015)	• Decision mining application to identify cost-effective possibilities for disease treatment and cost savings for patients (Rozinat & van der Aalst 2006) • Scatter diagrams representing visually specific measurements of patients on a relative time scale (Klimov et al. 2014)	• Role hierarchy miner to discover and match employees talents with roles (Bozkaya et al. 2009) • Discovering data-aware declarative process models which combines both case and process data to predict future events (Maggi et al. 2013)	• Pattern and temporal extraction: data mining techniques for classification and segmentation of patients and diseases (Bose & van der Aalst 2009; Moskovic & Shahar 2009) • Fuzzy miner: a technique for creating a process map that automatically cluster activities such as insurance claims historic payments (Gunther & van der Alst 2006).

The main reason for the high investment in IT-enabled A&BI systems, techniques and process in the support activities of the new value chain activities of healthcare organizations can be attributed to the paradigm shift in focus on care delivery. Base on the new ACO act, healthcare organizations are currently being more proactive and agile by providing care and services that are geared towards reaching the healthy masses of the population with advanced technology-driven systems, techniques and process. Hence, the increasing trend in investment on information technology-driven analytics and business intelligence systems that will enable management of healthcare organizations remotely monitor and influence decisions of their consumers. This is expected to enable them cut cost on care delivery and services that have in the past been predominantly provided within hospital and care facilities, reduce emergence room (ER) congestion, and avoid penalty payment to government and other stakeholders by ensuring consumers continue to live healthy and are continuously provided with services and recommendations that will keep them from coming to the hospital for treatment.

3.8 Study Implications

3.8.1 Managerial Implications

The revised healthcare value chain framework presents several practical implications to healthcare organizations. First, the study contributes to healthcare practice by developing a revised healthcare framework that is more current and clearly depicts contemporary healthcare value creation and delivery process that is now being driven predominantly by IT. In this regard, however, healthcare managers considering IT investments should consider systems that easily facilitate remote communication and engagement with the healthy majority of people in their communities. Viewing the current healthcare delivery practices through the lens of the revised HCVC framework can reduce the confusion around value creation mechanisms.

Second, the revised HCVC framework can be used to facilitate quality of care delivery, as well as offering better services to both healthy consumers as well as sick patients who need physicians' attention. This study's findings imply that effective value creation and delivery in current healthcare organizations rest on effective use of information technology and other information system related elements such as A&BI. These elements either directly or indirectly affect the awareness of value creation, motivation to act or respond, and the capability of healthcare organizations to act or respond proactively. By consciously evaluating the ways IT can be used to reach the masses of the population through effective flow of information, managers can avoid bottlenecks and anomalies across competitive value creation process that may hinder the opportunities to deliver quality of services to consumers.

Moreover, while this study's findings are mostly explanatory, they are also prescriptive. Thus, this research uncovered the notion that IT is indeed significantly transforming and reforming current healthcare delivery process from being hospital-centric to community-based caregiving. As a result, there has been a paradigm shift from the traditional way of value creation which used to be predominantly focused on how best to use hospital facilities and resources efficiently to deliver quality care, to how IT can effectively be utilized to remotely track consumer health behavior.

3.8.2 Research Implications

Whiles several studies have sought to explain the mechanisms through which most organizations create and deliver value to their consumers, only few studies have focused on investigating how healthcare organizations are creating and delivering value especially through IT and A&BI. By using a case study approach to conduct a field study to investigate how IT is impacting healthcare value chain activities, this study helps discern how IT employees as well as managers collectively view the current process of value creation and delivery and the integral role played by IT and BI in that process. The revised HCVC framework depicted in Figure 4 can be used to explain, evaluate, or anticipate the role of IT in contemporary value creation and delivery processes healthcare organizations now go through. By using interview data, this study helps gain granular insight into IT-enabled A&BI value creation process and why it is important for healthcare organizations to adapt to this emerging process.

By providing evidence for, and then revising the HCVC framework to demonstrate how healthcare organizations are currently creating and delivering value, this study serves as a gateway and spur further research into this area. This should result in providing a foundation for further explanatory or theory developing research in terms of qualitative studies and theory validation in quantitative research. Lastly, this will not only help better inform research in healthcare but also, this study will help inform value chain maturity research within organizations in other industries.

Moreover, this research contributes to both IS and healthcare value creation streams of literature. Although prior research have primarily examined visible, detectable sources of value, no study has yet examined the processes that healthcare organizations go through in creating and delivering value to their consumers. This study is the first to evidently show the processes by which such value creation activities are carried out in the modern-day healthcare context. Most IS and healthcare research has, until now, assumed linear and hierarchical process by which healthcare industry creates and delivers value specifically within healthcare facilities such as hospitals, nursing homes, ambulatory services, etc. However, value creation and delivery these days goes beyond that which is realized solely through these facilities. That is, healthcare organizations are now proactively reaching out to even the healthier people within the communities through IT with the aim of helping them to continue to stay healthy. By providing this revised HCVC framework, this research provides a holistic or much broader view of how healthcare organizations value creation spun beyond the traditional facility-based approach to creating and delivering value.

3.8.3 Limitations and Future Research

It is important to admit the fact that there are few limitations that can potentially be viewed as fertile ground for future research. First, the value chain framework for population health (Figure 5) that was developed from this research is so tied to the data that the resultant outcome is likely to be consistent with empirical observation (Eisenhardt 1989). However, large-sample, statistically generalizable studies are needed to test specific aspects of the model.

Second, the resultant framework was developed through an in-depth examination of the contemporary value creation and delivery process carried out within a single but yet large healthcare organization. In this regard, the nature of value creation and delivery in this organization, and its particular utilization of IT in the process to create and deliver value through primary and support activities might not be the same for every firm. It is therefore important that large-scale studies that involve multiple organizations are carried out in the future in order to sharpen generalizability and further our understanding of the role of IT-enabled A&BI in this complex process.

Third, IT are being used to extend the traditional cognitive, temporal, and spatial boundaries on value-based decision making. Furthermore, managers are utilizing IT to objectively evaluate value creation alternatives and make certain rational decisions. However, more research is needed to fully understand how IT-enabled A&BI capabilities are created within healthcare context and how these capabilities can be used to improve overall healthcare performance which subsumes value creation and delivery.

In the following section, I elaborate on potential research areas with specific propositions for future research. It is important to inform readers that some of these propositions, for example *P1*, provide the basis for my second study which has extensively been investigated and empirically addressed in the second part of this dissertation.

3.8.4 A&BI Capabilities for Data-Driven ACOs

Integrated data is a fundamental resource to a successful ACO. However, data can only achieve its full value through effective use of analytic and business intelligence (A&BI) capabilities. In data driven ACOs, A&BI help to drive actionable information from the integrated financial, administrative, clinical, population health and research data elements that are all needed to measure accountability, performance and quality. ACOs can use A&BI tools and techniques to sort through data in a timely manner, manage population health, support clinical decision-making, and evaluate provider or patient performance using cost and quality indicators. Based on this, I suggest the following proposition worthy of future empirical research investigations:

Proposition (*P1*): A&BI capability will have a positive significant impact on the overall performance of healthcare organizations especially in ACO-based institutions.

Below are examples of specific areas where A&BI capabilities can be leveraged to improve overall performance in healthcare organizations.

3.8.5 A&BI Influence on Financial and Administrative Process

ACOs can use A&BI to stratify data, help to prioritize, distribute or monitor intervention activities and results. ACO teams can stratify data by demographics, health status, and behavioral or financial risk. As an example, to determine financial risk, ACOs can use predictive modeling to forecast which patients are likely to be most costly, and identify methods to manage these costs or account for these costs during financial planning. If revenue targets aren't met, an ACO can use A&BI to investigate the cause. For example, data from different departments or care sites can be analyzed to determine where costs are higher than anticipated along the care continuum. Using this intelligence, ACOs can target interventions or improve administrative processes at those sites to reduce costs.

Upon noticing that three percent of its patients account for approximately 80 percent of spending, a large healthcare delivery provider comprised of more than 20 hospitals worked with an A&BI consulting firm known as *Informatica* to find a solution. To better manage the patient population, the health system focused on creating a longitudinal record for patients that encompasses the entire continuum of care, incorporates all sources of information, and fosters business and IT collaboration.

Informatica provided the health system with an end-to-end data integration solution, establishing a unified platform for data integration, governance and management. With its new data capabilities, the health system has developed a flexible platform built to scale to its users and needs as data management capability evolve. Based on this practical evidence, supported by theoretical evidence discussed earlier in the literature review, I suggest the following proposition:

Proposition (*P2*): A&BI capability will have a positive significant impact on the financial performance and administrative processes outcomes in healthcare organizations.

3.8.6 A&BI Influence on Care Coordination Outcomes

Coordinated care is a fundamental component to success of healthcare organizations, more specifically ACOs. This success can be supported by A&BI capability which help to evaluated the effectiveness, efficiency, and workflow of providers and care transitions, as well as identify gaps in patient care. While many ACOs struggle with obtaining a trusted view of information across sources, A&BI can be leveraged to help determine the accuracy and reliability of communication among providers, allowing ACOs to identify gaps in data transfer, including lost or inaccurate information, miscommunication, and misaligned information systems.

For example, although a large multi-facility, multi-location health system that provides a variety of services in both urban and distant rural care sites in the New England area was supported by a sophisticated technology infrastructure, it had no single record of each patient's complete care experience. Instead, clinical encounters with individual providers were being recorded in different ways, resulting in inconsistencies in the data recorded and therefore complicating its value. In order to get something meaningful and valuable from the fragmented and inconsistent data, the health system needed to better ensure proper and reliable integration of information across the health system in order to achieve a 360^{o} view and coordinated care of its patients.

To accomplish this objective, the health care organization worked with Edgewater Technology Company to define a universal Patient Encounter data model and a logical design for data transformation and storage components, encountering the integration of crucial data from all sources into a unified data exploration environment. Recognizing the benefits of A&BI capabilities, the technology company (Edgewater) helped the healthcare organization to build an integrated database to enable more complex analytics. With its new data and A&BI model, the healthcare organization is better able to integrate, govern and manage its data and capture a more holistic view of its patients. As a result, the healthcare organization realized a number of benefits such as patient compliance, case mix intensiveness per individual providers or practice groups, and geographical distribution of patients. Based on this I put forward the following proposition:

Proposition (*P3*): A&BI capability will have a positive significant impact on care coordination outcomes in healthcare organizations.

3.8.7 A&BI Influence on Disease Management and Treatment

As ACOs work to deliver high quality, cost-effective care that enhances care and optimizes outcomes, it is imperative that ACOs leverage data to identify standardized approaches and best practices. A&BI techniques enable ACOs to evaluate and compare the effectiveness of new and different treatment options and identify those best practices. ACOs can optimize A&BI to examine the cost effectiveness of specific treatments by measuring costs against quality of care measures. As evidence-based practices evolve and new approaches to treatment are developed, ACOs can use A&BI to estimate the relative benefits of new medical interventions against the potential costs in terms altered workflows, costs for purchasing new technologies, administrative changes, and others.

Similarly, A&BI can support the management of chronic diseases by analyzing specific clinical pathways to determine which disease management methods optimize patient outcomes. By assessing the value and utility of the care provided to a population, ACOs can implement more effective care protocols and use resources more efficiently to achieve better quality of care, health outcomes, and overall patient experience. A&BI can also help ACOs to identify clusters of high-burden patient populations stratified by condition, geographic location, and demographic information. By identifying at-risk patients, ACOs can proactively educate them about a specific disease or receive targeted interventions. Based on this, I put forward the following proposition:

Proposition (*P4*): A&BI capability will have a positive significant impact on disease management and treatment outcomes in healthcare organizations

3.9 Conclusion

This study has examined how healthcare organizations value chain framework has significantly been impacted by the increasing adoption and use of information technology and related analytics and business intelligence systems. This has come about as a result of major changes in healthcare delivery services now aimed at keeping the population healthy and away from hospital facilities. Using open-ended semi-structured interview in a large healthcare organization with five affiliate care providing organizations, it was discovered that the existing HCVC framework is currently outdated and hence, there was a need to revise and update the framework to meet the current healthcare organizations' care giving practices under the new ACO regulation.

Consequently, a revised framework is empirically provided using findings from interview responses gathered from 30 interviewees comprising of health IT employees, healthcare executives, physicians, nurses, and other clinicians. The revised HCVC framework is more reflective of how healthcare organizations are currently creating and delivering value to consumers by remotely engaging the general population using IT to ensure that consumers stay healthy so that they don't have to come to the hospital for care services. The revised framework also showcases which specific IT enabled analytics and business intelligence systems, techniques and applications are currently being applied within various domains of the value HCVC framework.

It was also discovered that healthcare organizations are now investing more in IT-enabled A&BI in the support activity domain of their value chain framework than they are on the primary activity domain. The fundamental reason for the high investment in IT-enabled A&BI systems, techniques and process in the support activities of the new value chain activities of healthcare organizations can be attributed to the recent shifts in focus on care delivery that was introduce by ACO act. Thus, the new ACO act has propelled healthcare organizations to now be more proactive and agile in providing care and services that are geared towards reaching the healthy masses of the population with advanced technology-driven systems, techniques and process. As a result, healthcare organizations are currently investing more on information technology-driven analytics and business intelligence systems that is expected to facilitate remote monitoring of consumer behaviors and also help influence decisions of their consumers.

This revised HCVC framework will contribute significantly to both literature and practice. In the case of academia, the revised framework opens a great deal of research opportunities to refine or test the model. For healthcare practice, the revised framework will serve as a guide to other healthcare organizations that are currently in the process of transitioning from the old system or framework of value creation and delivery to the new system under the current ACA and ACO regulation.

One major limitation of this study is that respondents come from a single, yet large healthcare organization. In order to enrich the findings as well as for generalizability to other healthcare organizations of diverse characteristics, replicating this study across various healthcare organizations is warranted.

CHAPTER IV

STUDY 2: AN EMPIRICAL STUDY OF THE IMPACTS OF ANALYTICS AND BUSINESS INTELLIGENCE CAPABILITIES ON HEALTHCARE ORGANIZATION PERFORMANCE

4.1 Introduction

Healthcare organizations (HCOs) in the U.S. are currently under constant pressure to improve their performance by reducing cost of care and provide better service at the same time (Ward, Marsolo, and Froehle, 2014). Despite the increasing demand and high expectations, HCOs still have promising future due to their increasingly growing data and the widespread of analytics and business intelligence (A&BI) systems and technologies (Yang, Li, Mulder, Wang, Chen, Wu, Wang, and Pan 2015). The Center for Medicare and Medicaid (CMS) estimated that the healthcare sector represents a staggering 17.9% of U.S. gross domestic product (GDP), and that the U.S. spent $2.7 trillion, or $8,680 per person, on healthcare in 2011 (CMS, 2013). It is also revealed that the U.S. healthcare sector is one of the fastest growing industries in terms of data generation with great economic potentials (Gartner 2013). However, despite these prevalent opportunities to be derived from their massive data, HCOs are still struggling to find efficient ways by which to improve their overall performance with less resources and cost (Agarwal et. al., 2010; Reiner 2013; Sharma et al. 2014; Wang et al. 2016). This has resulted in creating a large value gap between cost and benefit as stakeholders in the healthcare industry constantly seek a better answer to key question: “how can HCOs realize performance improvement while providing better quality of services at a lower cost?”

Two major reasons for the value deficit in HCOs, according to Ward et al. (2014), are very obvious. First, despite heavy utilization of information technology (IT) in rapidly advancing the productivity of many industries (Rawley and Simcoe, 2012), IT adoption and the use of analytics and business intelligence (A&BI) techniques in HCOs have constantly lagged behind (Wang et al. 2016; Gartner 2013). Second, there is lack of alignment between business and IT unit strategy, resulting in the consumption of more resources and overuse rather than overall patient health and well-being (Elbashir, Collier, Sutton, Davern and Leech 2013). In terms of alignment, there appears to be a lack of shared understanding between IT and business managers (Elbashir et al. 2013). While the importance of shared understanding to strategic alignment has previously been widely recognized in the IS literature (Preston and Karahanna 2009), A&BI aspect in healthcare context is particularly understudied. Motivated by these limitations currently facing the healthcare sector, this study draws on resource-based view (RBV), IT capability, strategic alignment, and socio-materiality theories as the underlying theoretical lenses to investigate the impact of A&BI impacts on healthcare organizations’ performance (HCOsPerf) outcomes. Additionally, the study also aims to explore the influence of the alignment between A&BI and the existing HCOs business strategy on performance.

Analytics, according to the definition by Cortada, Gordon and Lenihan (2012, p.2), is “the systematic use of data and related business insights developed through applied analytical disciplines (e.g. statistical, contextual, quantitative, predictive, cognitive, other modes) to drive fact-based decision making for planning, management, measurement and learning”. Business Intelligence (BI), on the other hand, consist of the use of analytics and reporting technologies that provide managers with relevant and easy-to-use historical information, including key performance improvements (KPIs) and alerts such as revenue and performance per employee, that can enable effective decision making (Williams and Williams 2006). Given the close similarities in their definitions and purpose, analytics and BI (A&BI) are often used interchangeably and simultaneously in the literature (e.g. Chen et al. 2012) to imply “the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market, and make timely business decisions” p. 1166. Building on Chen et al. (2012) definition, Isik, Jones and Sidorova (2013) suggested a revised version of A&BI definition to mean “a system comprised of both technical and organizational elements that presents its users with historical information for analysis to enable effective decision making and management support, with the overall purpose of increasing organizational performance” p. 14-15.

Business and IT executives in various industries have recognized the potential of A&BI systems and techniques used to analyze and interpret the large volumes of business event data to support planning and control, decision making, and organizational performance improvement (Vijayan 2012). Recent studies have demonstrated the role of A&BI systems’ capability to support advanced management accounting and control systems (Elbashir et al. 2011), regulatory compliance, and risk management (Nasar and Bomers 2012; Starr, Newfrock, and Delurey 2003). These prior studies explain the large investments in A&BI systems by organizations in an attempt to unlock the potential of their massive data to generate benefits (Anderson-Lehman, Watson, Wixom, and Hoffer 2004). Expenditure on A&BI technologies and techniques have significantly increased over the last decade (Vesset 2001), and A&BI continues to be a highly-ranked concern of business executives and CIOs (Wixom et al. 2011; Luftman and Ben-Zvi 2011; Gartner 2011).

However, unlike other industries such as financial, retailing, telecommunication, etc., the healthcare industry currently lags behind significantly in taking full advantage of current and emerging state-of-the-art A&BI technologies, systems and processes (Ferranti, et al. 2010). Many healthcare organizations are struggling today with the implementation of A&BI techniques and technologies even though they invest in numerous analytics systems and applications with the goal of improving their processes and performance (Murdoch & Detsky, 2013; Shah and Pathak, 2014). Evidence from a survey also reveals that 60% of HCOs surveyed failed to develop a clear, integrated enterprise strategy and vision for analytics deployment across a broad range of functions (Deloitte Center for health Solutions, 2015).

One of the reasons for the less effort and the slow pace in A&BI implementation in healthcare organizations may be attributed to the lack of understanding of the economic potential of A&BI deployment (Groves et al. 2013; Murdoch and Detsky, 2013). Another major reason is as a result of lack of prior research studies that specifically helps understand how healthcare organizations can develop the needed A&BI

capabilities that are necessary to access and derive meaningful insights from their huge data (Kohli and Tan, 2016).

A systemic review of the extant literature reveals that several current studies have proposed models, typologies and domains to study the impact of A&BI on organizations (Chen et al. 2012; Holsapple et al. 2014; Wixom et al. 2013). Existing A&BI research has focused, to a large extent, on anecdotal evidence in proposing the relationship between A&BI and firm performance (FP) (Agarwal and Dhar, 2014; Mithas, Lee, Earley, Murugesan, and Djavanshir 2013). However, despite the strong appeal of the concept of A&BI use and FP, empirical evidence about how A&BI contributes to performance improvement is lacking in the context of healthcare (Abbasi, Sarker, Chiang 2016; Davenport et al., 2012; Kohli and Tan, 2016). Based on this substantiated evidence of lack of sufficient studies of A&BI influence on healthcare organizations performance, this study draws on theoretically grounded frameworks to address the following research questions:

1. what are the building blocks of A&BI capability in healthcare organizations?
2. how is this A&BI capability developed within HC organizations?
3. what are impacts of this A&BI capability on HC organizations performance?

This research views A&BI capability from socio-materialism theory perspective because it addresses complicated mixture of talent, technology and management (Kim, Shin, & Kwon, 2012; Orlikowski and Scott, 2008). Socio-materialism theory provides an understanding into how human dimensions, technology and management are intricately interlinked since social and material perspectives are inseparable in organization research (Orlikowski, 2007). Thus, based on the socio-materialism, RBV and IT Capability theories, this research presents an entanglement conceptualization of three dimensions of A&BI – i.e. human, technology, and management – that highlights the importance of complementarities between them for high-level operational efficiency and effectiveness for improved performance.

Moreover, existing research also highlights the importance of A&BI capability-business strategic alignment (A&BI-BSA), which is defined as the extent to which analytics strategies are aligned with the overall business strategy of the organization (Agarwal and Dhar, 2014; McAfee and Brynjolfsson, 2012). Using RBV as the underlying theory, some researchers have proposed that internal business processes could be important factors linking A&BI and HCOs performance (HCOsPerf) (Dehning and Richardson, 2002; Melville, Kraemer, and Gurbaxani 2004). Given that A&BI-BSA is one of the important aspects of internal business processes in the organizations' response to market changes, (Davenport and Harris, 2007), this study is motivated to explore the role of A&BI-BSA by answering the research question:

4. does A&BI-BSA moderate the relationship between A&BI and HCOsPerf?

To address these research questions, this study develops and validates an A&BI capability model, and tests the direct effect of A&BI on HCOsPerf as well as the moderating effect of A&BI-BSA on the relationship between A&BI and HCOPerf. The study proceeds as follows: first, it begins with overarching review of the literature to further justify why A&BI is lacking, and for that matter, needed in the healthcare sector. Second, the study focuses on the underlying theories, conceptual model and hypotheses development. Third, on the methodology with emphasis on data collection, analysis and findings. The study concludes with a discussion on the theoretical and practical contributions, and provide guidelines for future research.

4.2. Literature Review

The Affordable Care Act (ACA) and the Health Information Technology for Economic and Clinical (HITECH) Act – a component of the American Recovery and Reinvestment Act (ARRA) of 2009) – have initiated a tremendous change in healthcare. Since the enactment of this major reform, hospital adoption of at least basic electronic health records (EHRs) has nearly doubled from 2009 to 20012, with about 44% of U.S. hospitals using at least a basic EHR (DesRoches, Charles, Furukawa, Joshi, Kralovec, Mostashari, Worzala, and Jha, 2013). This widespread of EHR adoption has set the stage for electronic data collection and subsequent analysis. The next phase entails transforming these data into actionable insights that can be used to improve healthcare delivery and performance.

One of the promises of EHR is the ubiquity of clinical and patient data available for research to improve medical decision-making and healthcare policy making. The increasing availability of health-related data coupled with advancements in technology has brought analytics and business intelligence to the attention of many healthcare organizations (Thayer, Åhs, Fredrikson, Sollers, and Wager 2012). Moreover, according to Kauffman, Srivastava, and Vayghan (2012, p.85), the healthcare industry, like many other industries, are constantly challenged by this big data concept "due to the increasing usage of social networking, the internet, mobile technologies and all kinds of other emerging technologies that create and capture data." Indeed, HCOs are currently overwhelmed by massive data which basically includes clinical and administrative data (e.g. structured data from patients' diagnosis of a diabetes, patients' profiles); clickstream data (e.g. web and social media content – tweets, blogs, Facebook wall postings, etc.); video data (e.g. collected through security cameras in the hospital premises); and voice data (e.g. data from phone calls, call centers, etc.)

Despite the great abundance of data and the limitless opportunities that comes along with it, many healthcare organizations currently lack the expertise, appropriate technologies, and key business management processes or techniques (such as analytics and business intelligence, data mining and machine learning, knowledge management, intuitive reporting systems, etc.) needed to maximize this invaluable resources (Wickramasinghe and Schaffer, 2006; Wang et al., 2016). Thus, the healthcare industry is currently faced with the need to be smarter by making data-driven informed decisions to improve care outcomes (Cortada et al. 2012).

It turns out, however, that the solution to the current challenges facing the industry potentially lies in the ability to develop and deploy the appropriate analytics and business intelligence (A&BI) capabilities (Gartner, 2013; Wang et al. 2016). In order to harness A&BI potentials, investments may be required to develop capabilities across business unit (Grossman et al., 2010). Human resources or human capital is another aspect of analytics that healthcare organizations need to invest more in as there have been a limited supply of analytics talent in the industry as a whole. Although analytics tools, technology, and infrastructure are indispensable, the right people with deep understanding of the business needs, desired goals, and objectives are equally crucial for the success of analytics deployment. People with analytics talents/knowledge are capable of deploying their knowledge, skills, and the appropriate tools to provide current and relevant information to decision makers and other stakeholders at all levels in the organization.

Davenport (2013) classified A&BI into three distinct types, namely: descriptive analytics, predictive analytics, and prescriptive analytics (Gartner 2014). Descriptive analytics uses reporting tools and applications to understand *what* has happened in the past and to classify and categorize historical, usually structured data. According to Kohli and Tan (2016), descriptive analytics can use aggregate electronic health records (EHR) data to answer such question as “What is the demographic distribution of diabetic patients? Predictive analytics utilize the understanding from the descriptive analytics, combined with new data into the EHR to predict patients who are likely to experience health-related event. Predictive analytics answer questions such as “What is the likelihood that someone of a particular demographic type will become diabetic?” Lastly, prescriptive analytics build upon information from predictive analytics to identify patients who are at-risk and to recommend an optimal solution. Prescriptive analytics answer questions such as “What can a person do to avoid developing diabetes related complications in order to intervene?

Analytics and business intelligence (A&BI) are creating new business opportunities for companies and high demand for people who can analyze and use massive data. For example, a 2011 study by the McKinsey Global Institute predicts that by 2018 the U.S. alone will face a shortage of 140,000 to 190,000 people with deep analytical skills as well as 1.5 million managers and analysts to analyze huge data and make decisions (Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh, and Byers 2011). According to McKinsey (2012) report, companies that are currently using A&BI are expected to generate about 60% improvements in retail operating margins, 8% reduction in (US) national healthcare expenditures, and $150M savings in operational efficiencies.

Since A&BI became popular both in the literature and practice in recent years, interest in A&BI has heightened, leading to the proliferation of several different definitions, measures, conceptualizations and underpinning theories (Macey and Chneider 2008; Bailey, Madden, Alfes, and Fletcher 2015). While the increasing interest in this topical area is good for the enrichment of the content in literature, the diversity of such several views as well as the inconsistency in theoretical conceptualization are creating a big confusion in literature regarding the definition, level-of-analysis relevant to develop higher order constructs, and the use of appropriate measures that map onto the theoretical definition of engagement (Barrick, Thurgood, Smith, and Courtright 2015).

For example, studies have examined the relationship between A&BI as a unidimensional construct and its influence on firm performance (Pospiech and Felden 2012; Shmueli and Koppius 2011; Chau and Xu 2012). The results turn out to be mixed, with unclear association between A&BI dimension and firm performance (Chen et al.

2012; Davenport 2013; Phillips-Wren et al. 2015). Moreover, various definitions of A&BI have emerged in the both academic and practitioner literature (Isik et al. 2013). While some broadly define A&BI concept as a holistic and sophisticated approach to cross-organizational support (Alter 2004; Moss and Atre 2007), others approach it from a more technical point of view (Burton, and Hostmann 2005). Moreover, while some researchers use formative model to measure A&BI capability (Isik et al. 2013; Elbashir et al. 2013) no study has yet modeled it as a reflective multidimensional construct.

In this study, I seek to integrate these opposing views and perspectives in the definition, conceptualization, and modeling of the A&BI construct and propose a new research model that basically defines A&BI capability as an aggregate third-order multi-dimensional construct. Thus, based on theoretical foundations coupled with extensive review of the literature, I argue that A&BI capability manifests itself in three dimensions namely: 1) human (e.g. analytics knowledge or skill), physical (i.e. IT infrastructure), and organizational (i.e. management support). Exemplary study by Davenport et al. (2012) emphasize that the focus should be on: (i) management capability across core business and operations functions; (ii) data scientists in terms of human resource capability; and (iii) advanced IT infrastructure capability (e.g. open-source platforms such as Apache Hadoop, and cloud-based computing). McAfee and Brynjolfsson (2012) identify critical obstacles of A&BI as being lack of talent and its management, IT infrastructure, and decision-making capability across different functions. In like manner, Barton and Court (2012) propose the following three dimensions of A&BI capability: (a) appropriate management of data and its ability to predict and optimize models; (b) IT infrastructure to manage multiple data sources; and (c) the expertise of front line employees in understanding and effectively using the tools.

Moreover, Kiron, Prentice, and Ferguson (2014) focus on management culture, data management infrastructure, and skills as key components to consider in developing A&BI capability. In another recent study, Wixom et al. (2013) recognized A&BI capabilities in terms of strategy, data and people. Phillips-Wren et al. (2015) also suggested in their study that the current proliferation of massive data also adds new dimension to A&BI. Thus, it brings about enhanced opportunities for insight but also requires new human and technological resources and expertise due to its unique characteristics. Given these related prior studies, it is evident that majority of scholars agree that the key dimensions of A&BI capability comprise of effective management, infrastructure capability, and talent capability. Table 10 below summaries the related literature on A&BI that have been explored.

Table 10. Related Studies Supporting Multi-Dimensional Form of A&BI Capabilities

Related studies	**Talent Capability**	**Technology Capability**	**Management Capability**
Barton and Court (2012)	Talent (e.g. capability to build analytics models for predicting and optimizing outcomes.	IT platforms and data (volume, variety, veracity, etc.)	Management (ensuring appropriate fit between models and data)
Davenport et al. (2012)			

	Human resource capability (e.g. Data Scientists, Statistician, etc.)	Open source platforms (e.g. Hadoop and cloud-based computing) ensuring connectivity, compatibility and modularity.	Management of analytics at core business and operational functions.
Kiron et al. (2014)	Analytic talent, technical and business knowledge, effective dissemination of insights by organization.	Compatibility of analytic technologies, collaborative use of data (connectivity), and organizational openness.	Analytics planning, sharing and coordination, investment, control on analytics.
McAfee & Brynjolfson (2012)	Skills and knowledge of data scientists.	IT infrastructure	Corporate strategy
Ransbotham et al. (2015)	Talent (e.g. domain knowledge, statistics and other technical skills.	Infrastructure and process (e.g. machine learning, data management and information systems) to provide data quality.	Management (e.g. planning options, coordination between analytical producers and managers, model-based decisions and control.
Wixom et al. (2013)	People (e.g. capability to use basic reporting and ad hoc query tools, performance management dashboard applications,	Data (e.g. data model, standard and control)	Strategy (e.g. pricing, cost, productivity, service.

	customer facing web portal applications, etc.)		

4.3 Theoretical Background

To address the research questions above, this study draws extensively on a combination of multiple theoretical frameworks that focus predominantly on organizational resource allocation and utilization behavior. These theoretical lenses include: 1) resource-based view theory (Barney 1991); 2) IT capability theory (Sambamurthy and Zmud 1997); entanglement view of socio-materialism theory (Orlikowski and Scott, 2007); and the 4) Strategic alignment theory (Henderson and Venkatrama 1999). Detailed discussion about these theories and how they apply to this study are provided in the following section.

4.3.1 Resource-based View (RBV) Theory

The resource-based view (RBV) theory of the firm is one of the fundamental and widely used management theories. This theory is widely recognized as the gateway to achieving superior firm performance (Barney 1991; Akter, Wamba, Gunasekaran and Dubey, 2016). The theory's development was based on the fundamental assumption that "firms are profit-maximizing entities directed by boundedly rational managers operating in distinctive markets that are to a reasonable extent predictable and moving toward equilibrium" (Bromiley and Papenhausen, 2003; Leiblein, 2003). The theory recognizes the asymmetrically distributed nature of information about the future value of a resource. As such, firms in which managers are able to estimate the future value of their resources better than their competitors stand a higher chance of improving their performance and achieving sustained competitive advantage.

The theory proposes that if a firm is to achieve improvement in performance, then it must acquire and control valuable, rare, inimitable, and nonsubstitutable resources and capabilities, as well as have the organization in place that can absorb and apply them (Amit and Schoemaker, 1993; Barney et al., 2001; Kraaijenbrink, Spender, and Aard 2010). This assumption of resource heterogeneity indicates the capability of some firms in accomplishing certain functions with the help of their unique resources. The *valuable* dimension of resources enables a firm to enhance net revenues and reduce net costs (Barney and Arikan, 2001), which in other words helps firms to seize the opportunity to minimize threat (Barney and Hesterly, 2012). The *rare* dimension signifies the resources are possessed by a small number of firms to achieve competitive advantages. The *inimitable* dimension represents the inability of firms to directly copy or substitute such resources because they are costly to imitate. Studies have shown that *resource non-substitutability* signifies how difficult it is for competitors to replicate a firm's specific resources (Morgan, Slotegraaf, and Vorhies 2009; Akter et al., 2016). Finally, the *organizational* dimension focuses on the proper management of valuable, rare and inimitable resources to completely leverage its full potential (Barney and Clark, 2007).

Resources and capabilities are core elements and the building blocks of the RBV theory. While *resources* represent the tangible and intangible assets (e.g. human, organizational, technology, etc.), *capabilities* refer to the subsets of the firm's resources which are non-transferable and aim to enhance the productivity of other resources

(Makadok, 1999). Capabilities can also be described as tangible or intangible processes that facilitate the deployment of other resources and enhance overall productivity. In summary, capability represents special type of resources with the main objective to increase productivity of other resources within the firm (Morgan et al, 2009). According to the RBV theory, a firm's competency depends on its capabilities to effectively manage its resources to achieve firm's performance (FP) (Grant, 2002).

A&BI is one of the key organizational capabilities identified as the building blocks of competitive advantage in the current era of massive data availability (Davenport, 2006). As such, the characteristics of value, rarity, inimitability, and organization may become a source of superior firm performance (FP) (Akter et al., 2016). Peteraf and Barney (2003) defined firm performance as the creation of more economic value than the marginal competitor in its respective industry. Barney and Clark (2007) later extended the concept by adding "sustainability", which basically implies organization's ability to utilize its unique resources to create more economic value than marginal value and the competitors are unable to emulate such capabilities and relevant benefits.

Although RBV plays an important role in management research, there has been a lot of criticism about it as a result of its underlying static and tautological conceptualization, which have been addressed by theory refinements by other researchers (Akter et al., 2016; Makadok, 1999; Peteref and Barney, 2003). Below in Table 11 are several studies that have used and refined the RBV, which I draw on as a foundation for conceptualizing the dimensions of analytics and business intelligence capability (A&BI)

and predicting HCOsPerf. A thorough review of the literature suggests RBV as a compelling framework for integrating dissimilar A&BI dimensions, their synergistic effects on FP and the extent of business strategic alignment associated with this overall capabilities-performance relationship. Apparently, there is limited research on analytics and business intelligence (A&BI) that sheds light on conceptualizing the capability requirements that are critical for predicting firm performance (Abbasi et al., 2016; Akter et al., 2016; Phillips-Wren et al., 2015).

Thus, this study draws extensively on the RBV theory to argue that healthcare organizations performance in this modern era of data economy is enhanced only when capabilities are valuable, rare, inimitable, and when the healthcare organization or management exploits the potential of resources.

Table 11. RBV Theory Definitions and Foundation

RBV Theory	Definition	Sources Component
Resources	Resources are defined as tangible and intangible assets used by the firms to conceive of and implement its strategies	Barney and Arikan (2001)
Capabilities	A subunit of resources that is organizationally-embedded, non-transferable, firm specific, and used purposely to improve the productivity of other resources possessed by the firm.	Makadok (1999)
Valuability of resources	A resource that enhance firms' economic performance by enabling firms to cut down cost and/or improve revenue generation. For example, studies show that relational resources reduce the cost of serving customers over time, enhance profit, and increase loyalty.	Reinartz and Kumar (2003), Morgan et al. (2009), Verhoef et al. (2001).
Rarity of resources	Define as the varying level of ownership among firms within an industry with few firms possessing very low and others not possessing anything of such resources at all. Rarity, in other words, implies scarcity of resources possessed by few firms. The logic of passing the test of rarity is essentially passing the test for imperfect inimitability.	Makadok (1999), Crook et al. (2008)
Inimitability of resources	The long term sustainability of resources is determined by the extent to which competitors can easily replicate it at an acceptable cost. In other words, resource inimitability is a critical assumption which is based on historical conditions (e.g. patents), social complexity, (e.g. supply chain integration management using real-time data, and causal ambiguity (e.g. knowledge of data scientists embedded in relational resources).	Makadok (1999), Crook et al., (2008)
Organization		Kozlenkova et al. (2014)

Heterogeneity of resources	The structure and processes of an organization play a crucial role in shaping value, rarity and inimitability of resources in order to enhance firm performance.	Peteraf and Barney (2003)
Complementarity of resources	Explains how strategic resources are distributed unevenly across firms or how different firms possess different bundles of strategically relevant resources	Morgan et al. (2009)
Immobility of resources	This is defined as the extent to which the outcome of one resources is affected by the presence of another resource.	Barney and Hesterly (2012)
Competitive advantage	The difficulty of trading resources across firms, which essentially allows the benefits of heterogeneity of resources to remain over time.	Peteraf and Barney (2003)
Sustained competitive advantage (SCA)	A firm is said to achieve competitive advantage position if it is able to “create more economic value than the marginal (breakeven) competitor in its product market” (p. 314).	Barney and Clark (2007)
	A competitive advantage is said to be sustained if a firm is constantly creating more economic value than the marginal firm in its industry and when other firms are unable to emulate or replicate the benefits of this strategy (p. 52).	

4.3.2 IT Capability

IT capability role has been extensively researched in Information Systems (IS) which essentially extends to our knowledge about the role of technology in enhancing firm performance. IT capability is a firm’s ability to acquire, deploy, combine, and reconfigure IT resources in support and enhancement of business strategies and work processes (Sambamurthy and Zmud 1997). IT capability is critical for a firm to realize business value and sustain competitive advantage. Although research has begun to link firm-wide IT capability to competitive advantage (Bharadwaj 2000; Bhatt and Grover 2005; Mata et al. 1995; Ross, Beath, and Goodhue, 1996), there is still limited understanding of IT capability and how it relates to A&BI capability in contemporary business environments (Kohli and Grover 2008). Research to date is primarily conceptual or case study oriented. Thus, there is a need for further rigorous empirical examination of the relationship between IT capability and A&BI capability.

The literature on IT capabilities draws heavily on the RBV theory to argue that competence in leveraging IT-based resources is key source of competitive advantage and differentiates firm performance (Bharadwaj, 2000, Piccoli and Ives, 2005). Prior studies that have investigated the relationship between IT capabilities and firm performance using RBV as a theoretical framework have generally confirmed both direct (e.g. Bhatt and Grover, 2005; Powell and Dent-Micallef, 1997) and indirect (e.g. Pavlou and El Sawy, 2006; Tippins and Sohi, 2003) positive associations. Given that robust IT capabilities are indispensable and key dimensions in the current environment of ubiquitous data and business analytics, the level of their applications in various business functions can differentiate firm performance (Davenport, 2006). In other words, research increasingly highlights the role of distinctive IT capability to mobilize and deploy IT-based resources in combination with other organizational resources and capabilities to influence firm performance (Akter at al. 2016).

Reiterating the role of IT capability on firm performance in massive data environment, Davenport et al. (2012) stated that, “as data continue to evolve, the architecture will develop into information ecosystem - a network of internal and external services continuously sharing information, optimizing decisions, communicating results and generating new insights for businesses.” Current review of studies in the extant literature in data and analytics domain reveals that most prior studies of A&BI take advantage of the RBV theory using IT capability dimensions. In this regards, we present exemplary studies in Table 12 that shows relevant research on IT capabilities that utilize the RBV as a theoretical foundation and the nature of their subsequent relationships with firm performance.

Table 12. IT Capability Studies that Utilized RBV Theory

Types of IT Capability Studies	**Relationship between IT Capability and Firm Performance**	**Study Type**	**IT Capability Studies using RBV Theory**
IT capability and firm performance	Direct relationship	Empirical	Bharadwaj (2000), Santhanam and Hartono (2003)
IT capability	Direct relationship	Conceptual	Mata et al. (1995), Ross et al. (1996)
IT competency, organizational learning	Indirect relationship	Empirical	Tippins and Sohi (2003)
IT leveraging competency, dynamic and functional process	Indirect relationship	Empirical	Pavlou and El Sawy (2006)
IT management capability, IT infrastructure capability	Direct relationship with the higher-order	Empirical	

and IT personnel capability	IT capability construct and firm performance		Kim et al. (2012)
Managerial IT capability and alliance performance	Direct relationship	Empirical	Lioukas et al. (2016)
IT management capabilities, IT personnel expertise	Indirect relationship	Empirical	Kim et al. (2011)
IT infrastructure quality, IT business expertise, IT relationship infrastructure	Direct relationship	Empirical	Bhatt and Grover (2005)
IT human resources, technology resources, business resources	Direct relationship	Empirical	Powell and Dent-Micallef (1997)

4.3.3 Entanglement View of Socio-Materialism Theory

This study also draws on the sociomateriality theoretical framework which essentially refers to the ontological integration of social and material aspect of an organization (Akter et al. 2016; Orlikowski and Scott, 2008). The study is situated in this theory because it embraces the relational ontology of sociomaterialism which suggests that organizational (i.e. A&BI management), technical (i.e. IT infrastructure), and human (e.g. analytic knowledge or skills) dimensions are so intertwined that it is difficult to measure their contributions in isolation (Orlikowski and Scott, 2008). Orlikowski (2007) clarifies that “the social and the material are inextricably related” (p. 1437). Based on this fundamental theoretical underpinning, I argue the A&BI dimensions do not act in isolation, but rather, act together due to the interconnection that exist within them. This view also asserts that no properties are native to each constituent dimension because

A&BI dimensions are constitutively intermingled (Orlikowski, 2007) and mutually supportive (Barton and Court, 2012). It is however important to highlight that the individual capability dimension is the manifestation of the overall A&BI building blocks although other dimensions also play critical role (Akter et al. 2016). Table 13 below presents a summary of entanglement view of socio-materialism theoretical building blocks, which in summary alludes to the fact that reality does not represent independent objects (social or material), but rather, the joint agency of both.

Table 13. Foundations of Entanglement View using Socio-Materialism

Building Blocks of the Entanglement View Theory	**Definitions using Sociomateriality (Latour, 2005; Orlikowski, 2007; Orlikowski and Scott, 2008; Stein et al. 2014)**
Sociomateriality	Social and material elements within an organization are so intertwined that they become inseparable.
Ontology	Human and non-human are inextricably entangled to work together.
Epistemology	Focus on heterogeneous networks and their insights rather than individual or artifacts.
Dynamics of human and non-human agents	The inherent inseparability between social and material agencies are treated the same for analytics purposes. The relationship is emergent and shifting because the boundary of relation is not fixed.
Unit of analysis	Socio-material practice, such as BAC is an emergent characteristic of social activities. It indicates boundaries between social (e.g. managerial, personal) and material (e.g. technology) dimensions are not fixed but enacted in practice.

Several related studies have used the socio-materialism theory to explain organizational behavior (Akter et al. 2016; Orlikowski and Scott, 2007; 2008). For example, Kallinikos (2007) explores information growth and states that data, information and knowledge are entangled, and that hierarchical organizational resources could be leveraged through their synergistic ties. This view is not different from the prior literature on the RBV theoretical conceptualization. The RBV believes in achieving sustained competitive advantage by accumulating heterogeneous resources (Barney, 1991; Peteraf, 1993) in an organization through *complementarity* of resources and *co-specialization* (Powell and Dent-Micallef, 1997). Complementarity of resource refers to the situation whereby the value of one resource is enhanced by the presence of other resource (Powell and Dent-Micallef, 1997). Co-specialization, on the other hand, is defined as the situation where one resource has very little or no value without another (Clemons and Row, 1991).

In a nutshell, this study utilizes the *entanglement conceptualization* argument which essentially highlights the fact that A&BI dimension have both complementarity and co-specialization attributes, which act together in a synergistic manner to influence firm performance (FP). As far as our knowledge goes, there is currently paucity of research studies in the extant analytics and business intelligence literature that have explored and encapsulated A&BI dimensions by applying this theory of entanglement view under socio-materialism.

4.3.4 Strategic Alignment Theory

Lastly, this research also draws from the Strategic Alignment (SA) theory, which was originally developed by Henderson and Venkatrama (1999), to investigate how healthcare organizations are aligning their internal resources with the opportunities in the external environment by developing A&BI capabilities that enable them to derive the optimum value.

The concept of strategic alignment between corporate information technology (IT) strategies and business strategies has received a heightened research attention in both academic and practitioner IS literature (Boar, 1995; Grant, 2002; Henderson and Venkatraman, 1999; Reich and Benbasat, 2000; Van der Zee and De Jong, 1999). The theory was developed purposely for conceptualizing and directing the emerging area of strategic management of information technology. The theory has four fundamental dimensions namely: *business strategy*; *information technology (I/T) strategy*; *organizational infrastructure and processes*; and *I/T infrastructure and process*.

The theory's underlying argument is that the inability of corporate organizations to realize value from I/T investments is, in part, due to the lack of *alignment* between the business and I/T strategies. The theory demonstrates the alignment and integration between business and I/T in terms of two fundamental characteristics of strategic management: *strategic fit* (defined as the interrelationships between external and internal components of the business) and *functional integration* (which is the integration between business and functional domains).

There are two fundamental assumptions that drive the concept of organizational strategic alignment according to the theory. The first assumption is that economic performance is directly related to the ability of management to create *a strategic fit* between the position of an organization in the competitive product-market arena and the design of an appropriate administrative structure to support its execution (Henderson & Vankatraman, 1999). This assumption justifies the generally accepted claim that a company's strategic choices in both the internal and external domains should be consistent. The second assumption basically posits that this strategic fit is inherently dynamic. In other words, this assumption basically reiterates the fact that strategic alignment is not to be viewed as a one-time event but should rather be considered as a process of continuous adaptation and change.

Parker (1996) modified the original SA model by outlining the relationship that ought to exist between the overall business strategy, the IS/IT strategy, and the supporting business and IT infrastructures in order to derived the value thereof (Figure 8). Although the entire SA model and its associated constructs have received heavy criticisms from researchers as being too rigid, Hirschheim and Sabherwal (2001) debunked this claim by showing that the relationships between constructs are rather dynamic than they are static. Venkatraman (1997) attributes this dynamism to at least three factors: (1) the rapid advancement in technological and functional developments in IT infrastructure, (2) the renewed belief that IT can be instrumental in creating new business capabilities, and (3) the expanded market for IT products and services.

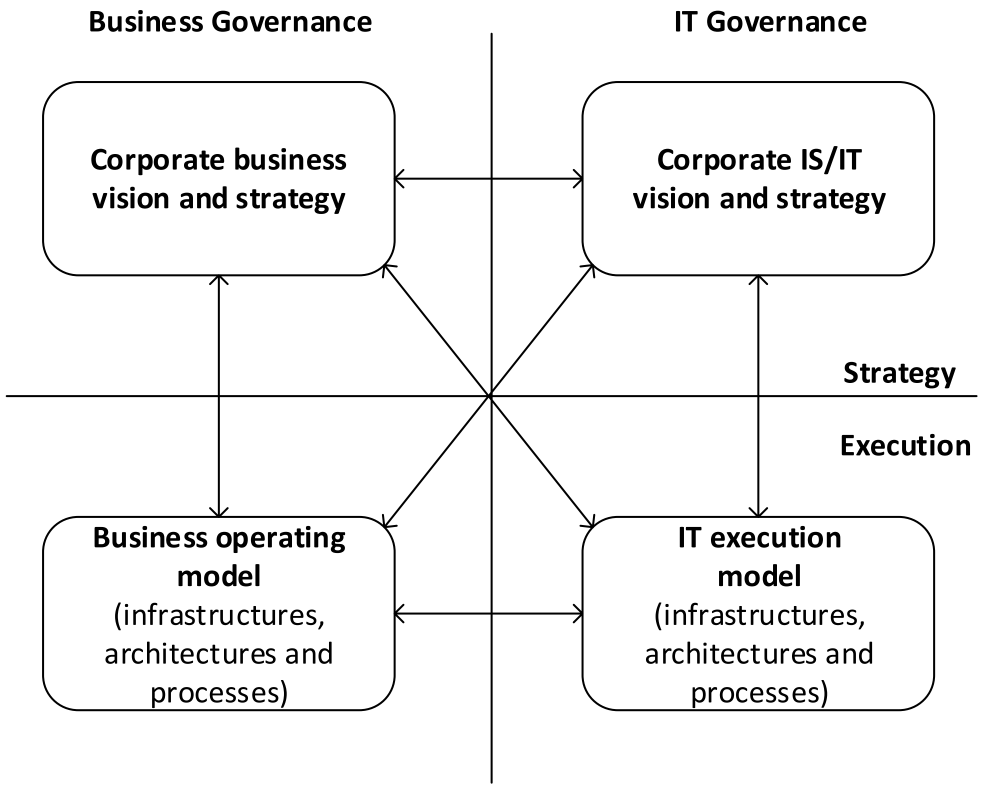

Figure 8. Strategic Alignment between Business and IT (Parker, 1996)

Basically, the strategic alignment model suggests that IT strategies should both derive from and shape business strategies in a dynamic environment (Henderson et al., 1996; Rockart, Earl, and Ross, 1996; Chan, Huff, Barclay, and Copeland, 1997). IT strategies derive from the business strategy in the sense that it seeks to articulate how IT can contribute to the achievement clearly defining business goals and objectives (Boar, 1995). IT strategy can shape business strategy on the other hand (Luftman, 1996; Hirschheim and Sabherwal, 2001). The capabilities inherent in ITs and related services provides numerous opportunities to business for creating, producing and delivering products and services. For example, the possibilities afforded by A&BI allowed organizations such as Amazon to pursue far-reaching enterprise integration strategies, something that would have been extremely difficult without the A&BI capabilities (McKinsey, 2012).

Strategic alignment between business and IT is not achieved only by the creation of well-developed and blended business and IT strategies. Reich and Benbasat (2000) argued that planned IT strategy is necessary but not sufficient contributor to effective alignment. Effective alignment is rather attainable on the combination of astute strategic planning and the effective execution of those plans (Boar, 1995). Effective execution is influenced largely by social constructs such as the level of communication between business and IT executives, the level of connection between business and IT planning processes and the level of shared domain knowledge between business and IT executives (Reich and Benbasat, 2000).

I draw from this theory to study how HCOs are strategically aligning their internal business with that of the emerging internal and external A&BI opportunities in order to derive business value.

4.4 Research Model and Hypotheses Development

Based on extensive review of the literature and interviews conducted with 30 A&BI employees of a large regional healthcare organization, I propose a conceptual research model that essential explains how healthcare organizations can develop superior A&BI capability which, in turn, can influence their overall performance. The study began by investigating commonly cited dimensions of A&BI that are essential for improving firm performance (Alismaili et al. 2016). The review revealed three key dimensions that reflect A&BI capability namely: A&BI talent capability, A&BI technology capability, and A&BI organizational management capability.

During the entire process of literature review and theoretical exploration, A&BI capability was frequently identified as a higher-order multidimensional construct, which suggested that several subdimensions would define the initially identified primary dimensions. As such, I conducted an in-depth longitudinal case study in a large regional healthcare organization with six (6) affiliate hospitals to explore how these multiple healthcare organizations are developing and deploying their A&BI capability in order to enhance their performance. Thus, I conducted extensive interviews with a total of 30 IT and top-level management employees of the healthcare organizations in order to further explore and verify the subdivisions of A&BI under each primary dimension identified during the literature review. The entire case study began in May, 2016 with respondents that represent a balance of analytics practitioners, consultants and top level management. Using this study, I found common agreement and support for a total of 12 subdivisions of A&BI's primary dimensions (i.e. talent capability, technology capability, and management capability) as proposed in the research model (see Figure 9). The 12 identified subdimensions are: technology management knowledge, technical knowledge, business knowledge, relational knowledge, planning, investment, coordination, control, connectivity, compatibility, modularity, and A&BI knowledge enhancement.

Drawing on the RBV, IT capability and entanglement view theories, I develop this research model (Figure 9) with the conceptualization that A&BI dimensions have the attributes of complementarity and co-specialization, which work together in a synergistic manner to achieve distinctive performance in healthcare organizations (Akter et al. 2016; Clemons and Row, 1991; Kim et al., 2012; Powell and Dent-Micallef, 1997; Tippins and Sohi, 2003). Each theory's complementarities are explained in Table 14 to illustrate how the RBV relates with the entanglement view of sociomaterialism, which altogether support the A&BI model.

The A&BI dimensions are conceptualized as distinct constructs even though they are interdependent and act in a way that mutually support and reinforce each other in the current massive data environment to realize business goals. Thus, this study presents an integrated approach to A&BI capability development and their alignment with business strategies for enhancing performance within healthcare organizations. In this regard, I identified subdimensions A&BI under each primary dimension based on the themes that emerged from the initial case study conducted. I henceforth present some literature findings in the following sections to support the case study findings.

Table 14. Theoretical Foundation Supporting A&BI Capability as Multidimensional

Theoretical Framework	Key Implications	Similarities with A&BI Model	Compliments to A&BI Model
Resource based view theory (Barney, 1991)	Resources are valuable, rare, imperfectly inimitable and supported by organizational structures and processes to enhance firm performance	In a like manner as RBV, A&BI depends on the assumption of resources heterogeneity, imperfectly mobile and inimitable resources, and also recognizes the importance of strategic alignment as key to effectively leverage the resources for influencing superior firm performance.	Management (ensuring appropriate fit between models and data) Management of analytics at core business and operational functions.
Entanglement view of using socio-materialism (Akter et al, 2016; Latour, 2005; Orlikowski, 2007; Orlikowski and Scott, 2008; Stein et al., 2014)	The relationship between human and material agencies is inseparable and inherently intertwined.	The proposed A&BI model relies on the building blocks of hierarchical capabilities (i.e. talent, technology and management). The entanglement view theory on the other hand shares the same view as the RBV theory which suggests that all the dimensions of A&BI are interrelated and mutually supportive.	Helps understand the logic of how people, systems, data, and management are entangled to influence firm performance. The hierarchical A&BI capabilities are leveraged through their synergistic ties which are based on complementarity and co-specialization.

Figure 9 below is the research model that was developed based on the extensive review of the literature and theoretical frameworks discussed above.

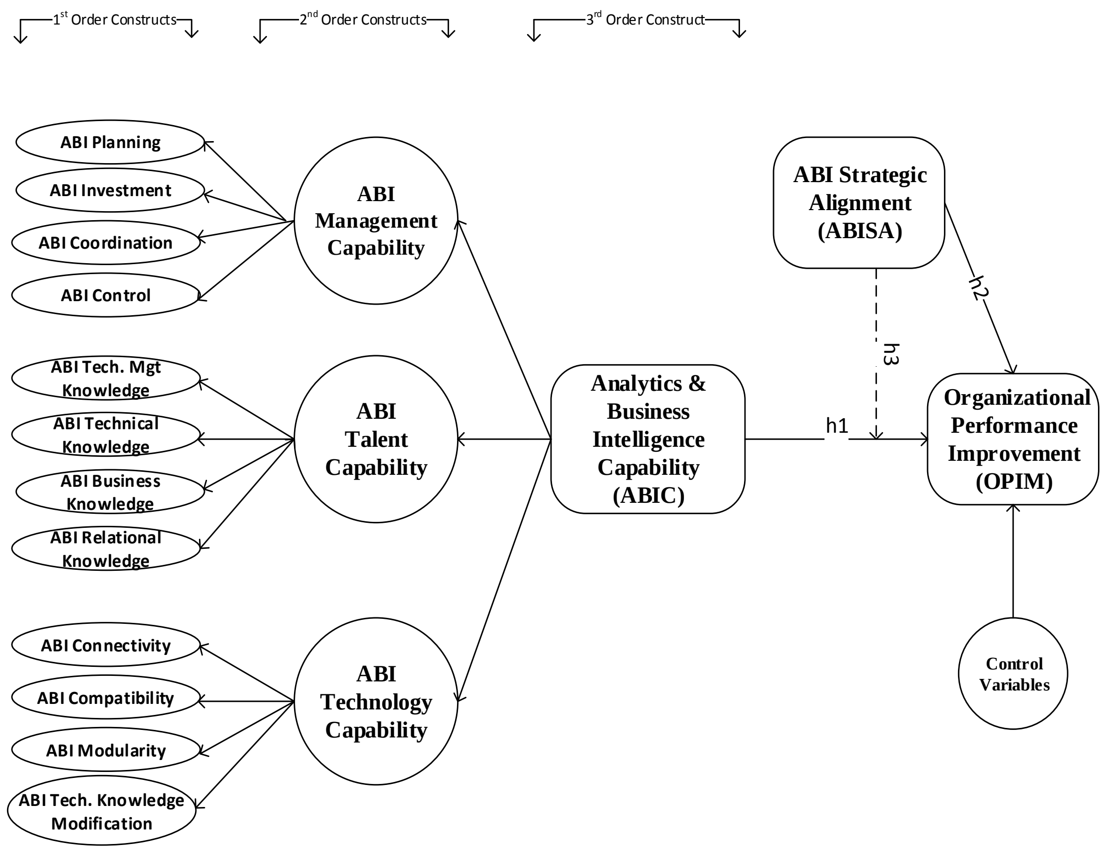

Figure 9. Research Model

4.4.1 A&BI Management Capability (A&BIMAC)

A&BIMAC is an important building block of A&BI capability ensuring that solid A&BI related decisions are made by applying proper management framework. Four core themes, based on the interviews as well as the literature findings, were found to constitute perceptions of A&BIMAC. These include (i) A&BI planning, (ii) A&BI investment, (iii) A&BI coordination, and (iv) A&BI control.

According to the healthcare organization's employees interviewed, ability for healthcare organizations to develop a very strong A&BI capability starts with the proper *A&BI planning process*. This A&BI planning process is critical in identifying business opportunities and determining how appropriate analytics models can apply to improve firm performance (FP) (Barton and Court, 2012). Similarly, *A&BI investment decisions* are also revealed to be core component of A&BIMAC as they reflect cost-benefit analyses. For example, Netflix Inc. transformed its A&BI by investing huge sum of dollars in web data of over one billion movie reviews in categories such as liked, loved, hated, etc. to recommend movies that optimize the ability to meet customer preferences (Davenport and Harris, 2007). In addition, *A&BI coordination* has received heightened attention lately in data and analytics environment, as being a form of routine capability that structures the cross-functional synchronization of analytics activities across firm (Kiron et al., 2014). For example, analysts of Procter and Gamble worked in coordination across operations, the supply chain, sales, consumer research, and marketing to improve total business performance (Davenport, 2006). Lastly, *A&BI controlling* is also extensively discussed as core to building organizational A&BI management capability. With this capability, organizations are able to ensure proper commitment and utilization of resources, including budgets and human resources (Akter et al., 2016). For example, Amazon's controlling function helps ensure thorough evaluation of A&BI proposals with regards to A&BI plans, clarification of the responsibilities of the A&BI unit, development of performance criteria for A&BI, and continuous performance monitoring of the A&BI unit (Schroeck, Shockley, Smart, Romero-Morales, and Tufano, 2012).

In summary, effective management of organizations' resources are important in developing A&BI capabilities (Raisch and Birkinshaw 2008). Organizations strategically orient itself by identifying and aligning individual performance with goals. Such strategic management characteristics help the organization to ensure that scarce resources are effectively allocated to ensure maximum return on investment.

4.4.2 A&BI Talent Capability (A&BITLC)

A&BITLC represents the ability of an analytics professional (e.g. someone with A&BI knowledge or skills) to perform assigned tasks in a huge data environment. This ability or "know how" is what is essentially referred to as "capabilities" that organizations use to create competitive advantage. Based on findings of literature and the case study, this study proposes A&BI as existing in three distinct but equally important skills sets: technical knowledge (e.g. database management, visualization tools and techniques); business knowledge (e.g. understanding short-term and long-term goals); and relational management knowledge (e.g. cross-functional collaboration using information).

Technical knowledge simply refers to knowledge about technical elements including database management systems and applications; programming languages; statistical knowledge, and operation systems. For example, data scientists at Google, Amazon, Walmart, eBay, LinkedIn, Yahoo, and Twitter have developed big data management systems using advanced technologies such as Apache Hadoop to transform their business analytics capabilities (Davenport and Patil, 2012; Akter et al., 2016). *Business knowledge* refers to the basic understanding of various A&BI-driven business functions and the business environment. For example, analytics professionals at Capital One Company have developed their feel for business issues and empathy for customers by creating customized products to meet the needs of different customers. With this practice, Capital One is having a growth of 20% annually (Bedeley et al., 2016). *Relational management knowledge* refers the ability of analytics professionals to communicate and work with people from other business functions.

Business analysts and data scientists need to have skills needed to build and maintain close relationships with the rest of the business. This skill has played a critical role in few organizations with a typical example being LinkedIn's ability to develop its new feature (e.g. people you may know) and achieving a 30% higher click-through rate. Thus, organizations, such as healthcare, looking to leverage the power of A&BI capabilities to improve their performance need to develop a balanced proficiency needs through ongoing training and coaching in managing the project, the infrastructure and knowledge (Barton and Court, 2012).

According to the RBV theory, employees' knowledge and skills: (i) enable companies to manage the technical and business risks associated with their investment in customer relationship management (CRM) programs (Bharadwaj 2000), (ii) are based on accumulated experience that takes time to develop (Katz 1974), and (iii) result from socially complex processes that require investment in a cycle of learning and knowledge codification. This makes it difficult for competitors to know which aspects of a rival's know-how and/or interpersonal relationships make them effective (Mata et al. 1995). Even though it may be possible for competitors to develop similar skills and experience, it takes considerable time for these capabilities to mature (Lado and Wilson 1994). As Grant (1996) observed in his study of the knowledge-based view, humans with unique abilities to convert data into wisdom can create competitive advantages that enhance firm performance.

4.4.3 A&BI Technology Capability (A&BITEC)

A&BI technology capability (A&BITEC) is a sub-construct of the overarching A&BI capability which refers to the flexibility in the use of A&BI platforms in terms of their connectivity of cross-functional data, compatibility of multiple platforms and modularity in model building. Three key themes are used to describe A&BITEC construct: connectivity, compatibility and modularity. Given the increasing constant demand for better care and service in the healthcare sector, it is imperative that healthcare organizations tackle volatile business conditions (e.g. changes in competition, market dynamics, or consumer behavior) and align appropriate resources with long-term and short-term business strategies (e.g. reasonable and relevant performance metrics, patient engagement, etc.). With a flexible A&BITEC, healthcare organizations can source and connect various data points from remote, branch, and mobile offices; create compatible data-sharing channels across various functions; and develop models and applications to address changing needs (Akter et al., 2016).

The flexibility of healthcare organizations A&BI capability depends on two main components: (1) *connectivity* among different business units in sourcing and analyzing a variety of data from different functions (e.g. patients' relationship management), and (2) *compatibility* needed to enable continuous flow of information for real time decisions. It helps clean-up operations to synchronize and merge overlapping data and to fix missing information. For example, Amazon ensures compatibility in the A&BI platform by using cloud technologies which help in collaboration, experimentation, and rapid analysis (Davenport and Harris, 2007). *Modularity*, on the other hand, embodies flexible platform development that allows the addition, modification or removal of features to, or from, the model as needed. It eventually helps with the creation of business opportunities and improving firm performance (FP) (Akter et al., 2016).

4.4.4 A&BI Capability and Healthcare Organization Performance

A&BI has been widely recognized as a core competency that is needed in every organization in order to increase business and firm performance (FP) in general (Jones, Cournane, Sheehy, and Hederman, 2016; Gartner 2013; Wixom et. al. 2013). A&BI provides a mechanism to methodically explore and visualize an organization's data (Jones et al., 2016). The literature provides evidence of a relationship between A&BI and FP in several cases. For example, Davenport and Harris, (2007) and Shroeck et al. (2012) have revealed in their studies how organizations are able to realize performance improvement by leveraging A&BI capabilities to optimize prices and maximize profit in return. Moreover, other scholars (Manyika, et al., 2011; Barton and Court, 2012; Columbus 2014; McAfee and Brynjolfsson, 2012; and Ramaswamy, 2013) have investigated and found a strong correlation between A&BI and sales growth, profitability improvement, market share increment, and return on investment (ROI).

In the case of healthcare, Srinivasan and Arunasalam (2013) show that A&BI can benefit healthcare organizations by reducing cost (i.e. reduced amount of waste and fraud, and improving quality of care in the areas such as safety and efficacy of treatment). In addition, McKinsey Global Institute (MGI) estimates that application of A&BI on large datasets possessed by healthcare organizations could save the entire U.S. healthcare system up to 30 billion dollars annually, with two thirds of that savings in a form of decreasing expenditures by 8%. Thus, by tapping into the vast real world observational data collected at the individual patient level, healthcare organizations can leverage the power of emerging A&BI technologies and techniques, extract subtle insights to enhance decision making (Hu and Wang, 2016).

A&BI capabilities also help facilitate clinical information integration and provide fresh insights to help healthcare organizations meet patients' needs and future market trends, and thus improving quality of care and financial performance. This implies that, healthcare organizations that creates superior A&BI should be able to maximize performance (FP) by facilitating the pervasive use of insights gained from its A&BI. Drawing on the RBV theory (Barney, 1991; Grant, 1991) and the relational ontology of sociomaterialism (Kim et al., 2012; Orlikowski; 2007; Orlikowski and Scott, 2008), I argue that A&BI significantly influences superior FP which is created as a result of unique combinations of organizational (i.e. A&BI management), physical (i.e. IT infrastructure), and human (e.g. analytics knowledge and skill development) resources that are constitutively entangled, valuable and difficult to imitate (Barton and Court, 2012).

Since IT is widely acknowledged as a critical component of A&BI, I also draw on the IT capability literature and argue that competence in mobilizing and deploying various A&BI resources differentiates healthcare organizations performance (*HCOsPerf*) and creates competitive advantage (Piccoli and Ives, 2005). Based on this fundamental reasoning, however, I propose the following hypothesis:

H1: *Analytics & business intelligence (A&BI) capability will have a significant positive impact on healthcare organizations' performance (HCOsPerf).*

4.4.5 A&BI-Business Strategic Alignment (A&BI-BSA)

Strategic orientation of the organizations are the contextual and structural policies and routines that firms utilize to carry out their business activities and is important in achieving superior firm performance (Raisch and Birkinshaw 2008). Organizations strategically orient themselves by identifying and aligning individual performance with goals. Such strategic management characteristics help the organization to ensure that scarce resources are effectively allocated in order to realize maximum return on investment.

A&BI and business strategic alignment (A&BI-BSA) have in recent times started to receive much attention from both academic and practitioners (Akter et. al., 2016). For example, Davenport et al., (2012) pointed to the fact that "key tenet of A&BI and the present ubiquity of data is that the world and the data that describe it are constantly changing, and as such organizations that can recognize the changes and react quickly and intelligently will have the upper hand." (p. 46). Owing to the uncertainties surrounding the true value from A&BI investments, strategy scholars and organizational stakeholders have always advocated establishing a strategic fit or alignment, viewing the firm as collection of resources that are interlinked by a specific governance structure (Peteraf, 1993).

A&BI-BSA is defined as the extent to which emerging techniques and processes of A&BI is aligned with or integrated into the overall business strategy of the organization (Akter et al., 2016). Alignment between A&BI and business strategy depends on visionary leadership which helps to synchronize capability with the functional goals and objectives. For example, McAfee and Brynjolfsson, 2012) pointed out that, “companies succeed in the massive data era not just because they have more or better data, but because they have leadership teams that set clear goals, define what success looks like, and ask the right questions. A&BI power does not erase the need for vision or human insight” (p. 66). Being one of the industries with rapidly growing data, the healthcare industry stands a greater chance of improving its overall performance with a larger amount of synchronization between A&BI and business strategies. This is because such synchronization will go long way to increase the synergy among different functional units which, ultimately positively impact individual organizational performance (Akter et al, 2016). As a result of such greater synchronization, it becomes possible to effectively and efficiently leverage A&BI by overcoming cognitive, structural and political barriers.

While strategic alignment may have received increased attention in the literature, (Akter et al., 2016; Davenport 2006; Garter, 2012; McAfee and Brynjolfsson, 2012), but not much is yet known about the direct impact of A&BI-BSA on healthcare organizational performance (*HCOPerf*) as well as on the relationship between A&BI-HCOPerf. For example, Barton and Court (2012) amplified this challenge organizations currently face in their study by stating, “many companies (including healthcare organizations) grapple with such problems, often because of a mismatch between the organization's existing culture and capabilities and the emerging tactics to exploit analytics successfully. In short, the new approaches don't align with how companies actually arrive at decisions, or they fail to provide a clear blueprint for realizing business goals." Based on this, I argue that A&BI-BSA capability is a unique and distinct capability which either directly or indirectly significantly contributes to healthcare organizations' overall performance by linking the right capability with a business need or problem to be address. Thus, I hypothesize that:

H2: *Analytic and business intelligence capability-business strategic alignment (A&BI-BSA) will significantly impact healthcare organizations overall performance.*

And I also theorize that:

H3: *Analytic and business intelligence capability-business strategic alignment (BACBSA) will moderate the relationship between A&BI capability and healthcare organization performance (HCOPerf).*

4.4.6 Control Variables

This study accounts for a set of control variables which include: size of organization (firm size), firm age, type of industry sector, and level of technology use. Although I acknowledge the possibility of their impact on competitive advantage, their individual influences are captured as controls in this study. For instance, prior studies (Armstrong and Sambamurthy, 1999; Liang et al. 2007) found that larger organizations have more slack resources that allow them to explore some innovative practices and absorb the cost of such exploration more easily than can smaller organizations. Similarly, type of industry is revealed in the literature to significantly impact the ability to achieve competitive advantage as a result of the variability in effective use of information across different industries. For instance, Kettinger, Zhang, and Chang (2013) explain how the role of information may be greater in supporting value-chain activities than in supporting business strategies in a manufacturing industry.

4.5 Research Methodology

This study was conducted mainly through the use of survey method to gather data from healthcare organizations with experience in the use of analytics and business intelligence technologies, techniques and processes. Although the unit of analysis is in the organizational-level, I collected survey data and used aggregate responses of employees in IT department, A&BI experts and senior business and IS executives in healthcare organizations. Below is a detailed information about data collection processes.

4.5.1 Scale Development

The study was conducted by adapting the measurement scales from prior literature and subjected to series of validation procedures in order to ensure content validity, construct validity, and reliability (Straub 1989) (see Appendix A). Scales were customized to fit the healthcare context of the study in order to ensure that they are applicable to all employees with A&BI experience including top level managers. Prior to carrying out the actual data collection, content validity of the survey questions used was conducted through a pre-test with 5 faculty members and 30 healthcare industry A&BI

experts including top-level management. Feedback gathered from participants of the pre-test shows initial construct validity with overall 85% agreement between participants that the measurement scales were meaningful and valid for measuring what they are intended for (Lu and Ramamurthy 2011). All ambiguous items identified were further examined and modified.

Next, the refined survey questionnaires were further pilot-tested with 48 healthcare organizations IT employees as well as top-level managers involved in A&BI initiatives, to ensure clarity of wording as well as reasonability of survey questions. In addition, interviews were conducted with 30 business and IS executives within a large healthcare organization to assess indicators, constructs and comprehensiveness of the instrument. This allowed the proposed model to be tested for robustness before the actual data collection. The questionnaires were further refined prior to the final launch of the survey.

All items were measured using a 7-point Likert scale. Certain relevant variables (e.g. *firm size*, *firm age*, *type of industry sector* and *extent of technology use* within study organizations) that may potentially influence organizational performance besides A&BI in healthcare were controlled for in order to avoid any potential bias that can possibly be introduced by these variables.

4.5.2 Data Collection and Preliminary Analysis

The survey was launched and managed by Qualtrics Survey Research Team on February 28, 2017. Unlike prior related studies, this research targets healthcare organizations that are currently investing in or utilizing A&BI initiatives to enhance their performance. In all, a total of 1878 healthcare organizations were initially contacted to respond to survey questions of which 965 panel members completed and returned their responses. After careful initial screening of the survey data obtained, it was discovered that only 194 completed and valid responses were useful, thus resulting in a response rate of 20.10%. A test for nonresponse bias showed no significant differences between responding and nonresponding organizations with regards to firm's geographical location and ownership type (private or public).

Table 15 below shows that of the total valid responses obtained, majority of respondents (37.24%) fall within 26-35 age bracket, followed by 36-45 age range with 28.06%. The remaining age ranges (18-25; 46-55; and 56+) all have percentage of respondents below 15% (i.e. 11.73%; 13.27%; and 9.69% respectively). From this finding, it becomes clear that our sample of response is dominated by people that can be classified as early to mid-career employees. With respect to gender, it turned out that 58.97% of the respondents are female while the remaining 41.03% are male. This implies that there are more female A&BI healthcare employees in our sample than their male counterparts. In terms of level of education, the demographic data results show that majority of the respondents (43.08%) hold a four-year college degree with either Bachelor of Science (BSc.) or Bachelor of Arts (BA), followed by postgraduate degree holders with either Masters or Ph.D. (33.85%). The remaining respondents hold either an associate degree from community colleges (16.67%) or high school diploma (6.67%).

With regards to years of A&BI experience, the descriptive analysis results show that majority of respondents (37.44%) have between 1-5 years of experience in A&BI,

followed by those with 6-10 years of experience (24.62%), then by those with 11-15 years of experience (15.90%). The remaining respondents have either less than one year of A&BI experience (6.15%), 16-20 years of experience in A&BI (8.72%), or 20+ years of A&BI experience (7.18%). With regards to firm size (i.e. number of firm employees), I found that majority of respondents (21.28%) come relatively large organizations with employees ranging between 500-1000.

In terms of firm age, I found that majority of respondents (37.23%) come from healthcare organizations that have been in business for at least 20 years. As for as type of industry is concerned, I found that majority of healthcare organizations (51.06%) that participated in the study belong to the public healthcare sector or category. Finally, as far as technology use is concerned, I found that majority of healthcare organizations (55.32%) that participated in the study fall within the high technology (*high-tech*) classification, implying that such HCOs heavily utilize technology or rely on A&BI related technologies, techniques and processes to achieve their daily business objective.

Table 15. Demographic Profile of Respondents and Control Variables.

Variable	Count	Percentage(%)
<u>Respondents Demographics</u>		
Age (in years)		
18-25	23	11.73
26-35	73	37.24
36-45	55	28.06
46-55	26	13.27
56+	19	9.69
Gender		
Male	80	41.03
Female	115	58.97
Education		
No formal education	0	0.00
High school diploma	13	6.67
Associate degree from community college	32	16.41
Four-year college degree (BSc., BA, etc.)	84	43.08
Postgraduate degree (Masters/PhD)	66	33.85
No. of years in A&BI experience		
Less than 1 year	12	6.15
1-5 years	73	37.44
6-10 years	48	24.62
11-15 years	31	15.90
16-20 years	17	8.72
20+ years	14	7.18
<u>Control Variables</u>:		
Control1: Firm size (No. of employees in firm)		
0-19	8	8.51
20-99	7	7.45
100-249	18	19.15
250-499	6	6.38
500-999	20	21.28
1000-2499	7	7.45
2500-4999	15	15.96
5000+	13	13.83

Control2: Firm Age (No. of years firm has in business)		
Less than 1 year	4	4.26
1-5 years	12	12.77
6-10 years	20	21.28
11-15 years	7	7.45
16-20 years	16	17.02
20+ years	35	37.23
Control3: Industry type		
Private healthcare	44	46.81
Public healthcare	48	51.06
Other	2	2.13
Control4: Technology use/reliance		
High tech	52	55.32
Moderate tech	36	38.30
Low tech	6	6.38

4.5.3 Operationalization of Constructs

Study variables were operationalized using multi-item reflective measures (on a seven-point Likert scale). Reflective indicators manifest (or are caused by) their latent constructs, are interchangeable, covary, and share common theme (Jarvis et. al. 2003; Lu and Ramamurthy 2011). Appendix A presents the final instrument.

Healthcare organization Performance (HCOsPerf): This construct was measured with six items that reflected value realized in healthcare organizations as a result of the implementation of analytics and business intelligence (A&BI) related technologies, systems or processes.

A&BI-business strategic alignment (A&BI-BSA): This construct was also measured with four items that reflected healthcare organization’s ability to align its internal business processes with A&BI systems for improved performance.

Analytics & business capability (A&BI): Consistent with our theoretical conceptualization, A&BI capability was modeled as third-order construct reflected in its three interrelated second-order dimensions which are each reflected in four distinct primary dimensions. Each of the four primary sub-dimensions of A&BI were measured with four different items that reflected A&BI's three second-order dimensions. This measurement model specification captures the common variances or covariances shared model among the dimensions (Venkatraman 1989).

Control variables. *Firm size* was measured as the firm-wide number of full-time employees (FTE) and *firm age* was measured as the number of years the company had been in business. *Industry sector* was measured by the type of industry type (private, public or other) that the company is identified with, and *technology use maturity* was measured by the extent to which the company is using, implementing or considering to begin using current and emerging technology tools, systems and process to improve performance.

4.6 Analysis and Findings

As was initially conceptualized, the study specifies that the mode of measurement is reflective as the first-order dimensions are reflective of the intermediate and higher order-dimensions (Chin 2010; Ringle, C., Sarstedt, M., Straub. 2012). Moreover, the model is reflective because the theoretical direction of causality is from constructs to items. Thus, the measures used in the study are manifestations of constructs, and as such, changes in the constructs cause changes in the measures.

4.6.1 Measurement Validation

This study presents measurement validations following Straub and Carlson (1989), Doll and Torkzadeh (1988), Nunnally (1978) and Nunnally and Bernstein (1994). I used previously validated measurement items wherever possible to help ensure the validity of my measurement. Multiple item measures were used for most constructs to enhance content coverage (Yli-Renko, Autio and Sapienza 2001). Convergent and discriminant validity of the scale was evaluated according to Nunnaly (1994), Chin et al. (2003), and Pavlou and Fygenson (2006). Prior studies have indicated that internal consistency for the constructs is further validated through composite reliability and Average Variance Extracted (AVE) (Fornell and Larcker, 1981; Tan, Benbasat, and Cenfetelli 2013). Typically, 0.70 is considered as the threshold of internal consistency for all variables (Nunnally and Bernstein, 1994; Pavlou and Fygenson, 2006). Most constructs exhibited high reliability (see Table 16) in our sample. Thus, the measurements fulfilled the requirement of convergent validity.

To overcome the concern for common method bias in the survey design, I first included several reverse-scored items in the principal constructs to reduce acquiescence problem (Pavlou and Gefen, 2005). I then used Harman’s one-factor test to assess common method variance after data collection (Podsakoff and Organ, 1986; Pavlou and Gefen, 2005. Further analysis indicates that there is no common method bias in our study.

4.6.2 Confirmation Factor Analysis

I performed confirmatory factor analysis (CFA) using LISREL 9.2 software to assess convergent validity and reliability. All the multiple-item constructs obtained

Cronbach alphas of .70 or higher, indicating strong internal consistency. Table 16 presents a summary of the CFA result, as well as the correlation and reliability of all latent constructs. Detailed CFA analysis of the independent variables or first order constructs are presented from section 4.6.3 to section 4.6.6. As shown in the results below, first, all indicators loaded high (>.70) on their respective constructs. Second, the fit indices of the measurement model were all within the normally specified threshold. Third, composite reliability for each construct was greater than .70, and the average variance extracted (AVE) for each construct was above .50. The square-roots of all AVEs were greater than the correlations between the respective constructs and the other latent constructs (Fornell and Larcker 1981; Hair, Anderson, Tatham, and Black, 1998). Together, these results provide evidence of reliability, convergent validity, and discriminant validity of the measures. Below is the detail results CFA analysis.

Table 16. Results of Confirmation Factor Analysis: Correlation and Reliability of Latent Constructs

Constructs	# of Items	Mean	SD	Latent Variable Correlations 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	Range of Factor Loadings	Cronbach Alpha	Composite Reliability	AVE
1. A&BI Bus KN	4	5.405	1.265	1																		.75 - .85	0.892	0.925	0.756
2. A&BI Control	4	5.293	1.377	0.821	1																	.79 - .83	0.884	0.920	0.742
3. A&BI Coordin	4	5.133	1.415	0.691	0.752	1																.79 - .83	0.878	0.916	0.731
4. A&BI Investm	4	5.441	1.314	0.719	0.718	0.719	1															.79 - .82	0.875	0.914	0.728
5. A&BI Plannin	4	5.304	1.398	0.703	0.784	0.639	0.726	1														.81 - .88	0.914	0.939	0.795
6. A&BI Rel KN	4	5.376	1.336	0.818	0.762	0.674	0.669	0.686	1													.76 - .90	0.888	0.923	0.749
7. A&BI Tech Mg	4	5.384	1.241	0.816	0.811	0.715	0.759	0.701	0.767	1												.73 - .82	0.869	0.911	0.718
8. A&BI Techcal	4	5.406	1.275	0.793	0.742	0.695	0.694	0.642	0.828	0.802	1											.78 - .84	0.876	0.915	0.729
9. A&BICompati	4	5.069	1.438	0.653	0.694	0.669	0.572	0.600	0.631	0.645	0.669	1										.70 - .80	0.842	0.894	0.680
10. A&BIConnec	4	5.084	1.457	0.675	0.751	0.739	0.620	0.643	0.699	0.706	0.711	0.790	1									.76 - .81	0.847	0.897	0.686
11. A&BIKnowU	4	5.089	1.492	0.690	0.686	0.725	0.653	0.635	0.706	0.699	0.720	0.697	0.713	1								.74 - .89	0.873	0.913	0.724
12. A&BIModula	4	4.924	1.474	0.634	0.689	0.722	0.657	0.597	0.615	0.687	0.651	0.720	0.701	0.734	1							.81 - .84	0.886	0.921	0.745
13. A&BI Org. M	4	5.293	1.379	0.825	0.916	0.869	0.885	0.889	0.784	0.839	0.778	0.712	0.773	0.757	0.747	1						.76 - .80	0.954	0.959	0.593
14. A&BI Talent	4	5.393	1.279	0.929	0.849	0.751	0.768	0.740	0.925	0.915	0.926	0.703	0.755	0.762	0.700	0.873	1					.74 - .81	0.961	0.964	0.629
15. A&BI Tech	4	5.042	1.466	0.744	0.791	0.801	0.703	0.695	0.744	0.769	0.772	0.896	0.896	0.884	0.888	0.839	0.820	1				.75 - .78	0.948	0.953	0.562
16. A&BI Cap	5	5.242	1.385	0.884	0.902	0.852	0.831	0.818	0.867	0.891	0.875	0.808	0.850	0.844	0.818	0.956	0.952	0.932	1			.86 - .92	0.981	0.982	0.534
17. A&BI - BusAl	4	5.375	1328	0.705	0.703	0.654	0.608	0.609	0.669	0.667	0.682	0.605	0.642	0.730	0.677	0.723	0.737	0.746	0.777	1		.72 - .83	0.883	0.911	0.631
18. Org Perf Imp	6	5.331	1.281	0.794	0.751	0.681	0.695	0.733	0.788	0.766	0.772	0.660	0.671	0.764	0.633	0.804	0.845	0.766	0.852	0.693	1	.72 - .80	0.868	0.910	0.717

4.6.3 A&BI Organization Management Capability

Below are the CFA results for analytics & business intelligence management capability.

Table 17. Covariance Matrix for A&BI Organization Management Capability

	Q7_1	Q7_2	Q7_3	Q7_4	Q8_1	Q8_2	Q8_3	Q8_4	Q9_1	Q9_2	Q9_3	Q9_4	Q10_1	Q10_2	Q10_3	Q10_4
Q7_1	2.181															
Q7_2	1.424	1.884														
Q7_3	1.500	1.474	1.989													
Q7_4	1.401	1.285	1.441	1.783												
Q8_1	1.060	1.053	1.070	0.981	1.577											
Q8_2	1.125	1.089	0.896	0.991	1.055	1.545										
Q8_3	1.108	0.942	1.038	1.043	1.106	1.028	1.806									
Q8_4	0.851	0.917	0.914	1.019	1.065	1.036	1.271	1.964								
Q9_1	0.860	0.869	0.937	0.932	0.834	0.843	0.838	1.101	1.661							
Q9_2	0.837	1.007	0.929	1.003	0.792	0.914	0.837	1.314	1.236	2.115						
Q9_3	0.717	1.209	1.038	1.002	0.987	0.806	0.966	1.302	1.281	1.467	2.326					
Q9_4	0.826	1.019	1.004	1.012	0.982	0.895	0.954	1.161	1.047	1.222	1.405	1.877				
Q10_1	1.077	1.323	1.276	1.124	1.025	0.837	0.861	0.978	1.066	1.077	1.405	1.253	1.928			
Q10_2	1.120	1.170	1.195	1.198	1.030	0.838	1.079	1.042	0.886	0.998	1.198	1.139	1.324	1.933		
Q10_3	0.981	1.076	1.216	1.084	0.942	0.746	0.873	0.900	0.822	0.829	1.096	0.980	1.088	1.280	1.729	
Q10_4	1.138	1.281	1.081	1.104	0.996	1.075	0.947	1.027	1.020	1.118	1.172	1.099	1.212	1.266	1.275	1.992

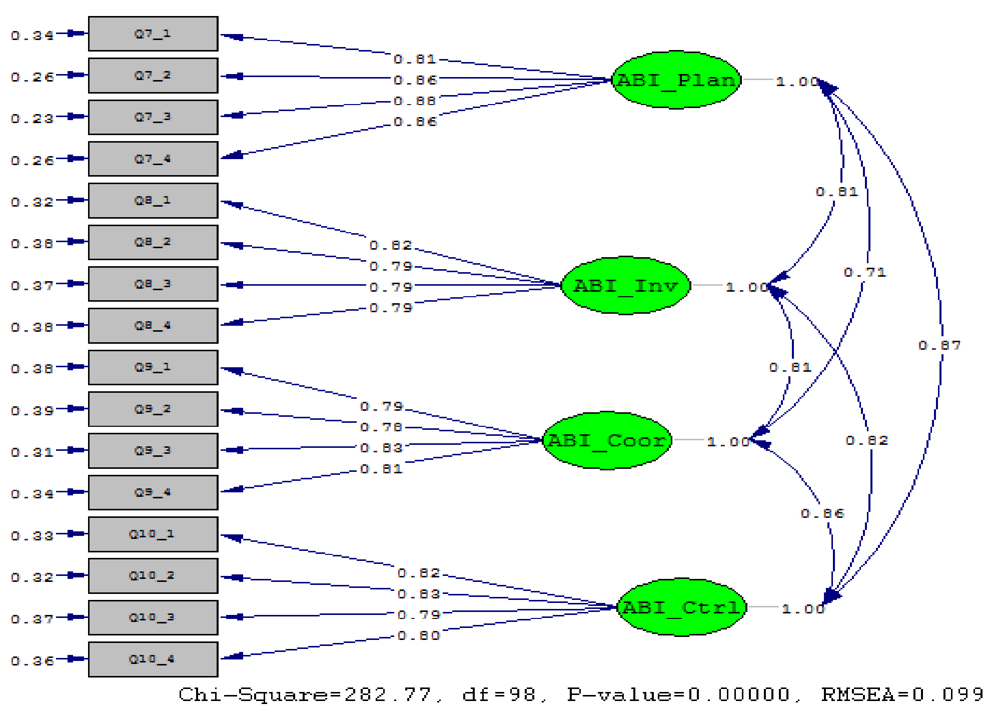

Figure 10. CFA Results for A&BI Organization Management Capability

Table 18. Fit Indices for Model 1

		RMSEA						
Model	**SRMR**	**LB**	**Estimate**	**UB**	**CFI**	χ^2	***df***	***p***
1	.047	0.085	0.098	0.112	0.975	282.77	98	0.00

Where No. of obs. → 194; SRMR → Standardized Root Mean Square Residual; LB → Lower Bound of 90% confidence interval; UB → Upper Bound of 90% confidence interval; CFI → Comparative Fit Index; χ^2 → Chi square estimate; *df* → degree of freedom; and *p* → *P*-value.

From the summary of the results presented above, it can be concluded that Model 1's chi-square test is significant. This implies that there is significant difference between the model's implied and observed covariance matrices (χ^2 = 282.77, *df*=98, *p*<0.00).

Also, RMSEA value was estimated to be 0.098 based on a 90% confidence interval with lower and upper bound ranging between 0.085 and 0.112 respectively. Comparing the estimated RMSEA to the ideal critical value of 0.05, it can be concluded Model 1 does not fit the data well enough because the model's estimated RMSEA together with its corresponding confidence interval bound are greater than the theoretically acceptable threshold (Kline 2010).

However, the model's SRMR value, which is estimated at 0.047, was found to be less than generally acceptable value of 0.08 according to Kline's (2010) text. This result implies that the model fits the data well since its correlation residual (0.047) falls below the acceptable threshold value (0.08).

Moreover, the model's CFI value (0.975) turns out to be greater than theoretically acceptable cutoff value (0.95) as suggested by Kline (2010). The implication of this result, however, is that the model fits the data very well because the greater the better.

In summary, because the model's SRMR, CFI and Chi-square results provide strong proof of good model-to-data fit, and because RMSEA value also suggest fairly good fit, it can be concluded that the overall fit of the model is good.

Table 19. Maximum Likelihood Estimates for a Recursive Path of Model 1

Path	Unstandardized	SE	Standardized	t-value
ABI_Plan → Q7_1	1.199**	0.089	0.812	13.532
ABI_Plan → Q7_2	1.180**	0.080	0.860	14.792
ABI_Plan → Q7_3	1.240**	0.081	0.879	15.343
ABI_Plan → Q7_4	1.146**	0.078	0.858	14.751
ABI_Inv → Q8_1	1.033**	0.076	0.822	13.606
ABI_Inv → Q8_2	0.981**	0.077	0.789	12.804
ABI_Inv → Q8_3	1.068**	0.083	0.795	12.924
ABI_Inv → Q8_4	1.102**	0.087	0.786	12.726
ABI_Coor → Q9_1	1.013**	0.080	0.786	12.726
ABI_Coor → Q9_2	1.133**	0.090	0.779	12.554
ABI_Coor → Q9_3	1.264**	0.092	0.829	13.772
ABI_Coor → Q9_4	1.109**	0.083	0.809	13.288
ABI_Ctrl → Q10_1	1.138**	0.083	0.820	13.674
ABI_Ctrl → Q10_2	1.148**	0.083	0.825	13.818
ABI_Ctrl → Q10_3	1.045**	0.080	0.795	13.055
ABI_Ctrl → Q10_4	1.125**	0.086	0.797	13.106

** $p < 0.001$

4.6.4 A&BI Talent Capability

Below is a summary of the CFA results for analytics & business intelligence talent capability.

Table 20. Covariance Matrix for A&BI Talent Capability

	Q11_1	Q11_2	Q11_3	Q11_4	Q12_1	Q12_2	Q12_3	Q12_4	Q13_1	Q13_2	Q13_3	Q13_4	Q14_1	Q14_2	Q14_3	Q14_4
Q11_1	1.690															
Q11_2	0.983	1.388														
Q11_3	0.884	0.996	1.490													
Q11_4	0.901	0.938	1.037	1.602												
Q12_1	1.138	0.935	0.894	0.919	1.733											
Q12_2	0.882	0.830	0.805	0.987	1.035	1.512										
Q12_3	0.809	0.868	0.819	0.879	0.918	1.039	1.598									
Q12_4	0.887	1.053	0.997	0.982	1.071	1.066	1.091	1.667								
Q13_1	0.842	0.722	0.911	0.864	0.829	0.787	0.695	0.750	1.420							
Q13_2	1.015	0.851	0.975	1.010	1.082	1.027	0.908	0.975	0.994	1.602						
Q13_3	0.934	0.812	0.985	1.180	0.970	1.046	0.982	0.969	0.955	1.144	1.677					
Q13_4	0.964	0.862	1.014	1.171	1.038	1.058	1.029	1.032	0.969	1.129	1.302	1.724				
Q14_1	0.939	0.843	0.881	0.929	1.050	1.038	0.907	0.939	0.923	0.883	0.988	1.095	1.670			
Q14_2	0.981	0.911	0.969	1.033	1.117	1.122	0.954	1.117	0.863	1.167	1.123	1.083	1.098	1.608		
Q14_3	0.908	0.879	1.019	1.072	1.144	1.183	1.058	1.167	0.883	1.279	1.136	1.202	1.084	1.437	2.022	
Q14_4	0.820	0.810	0.831	1.021	0.861	1.013	0.902	1.018	0.901	0.972	1.005	1.114	1.055	1.137	1.302	1.854

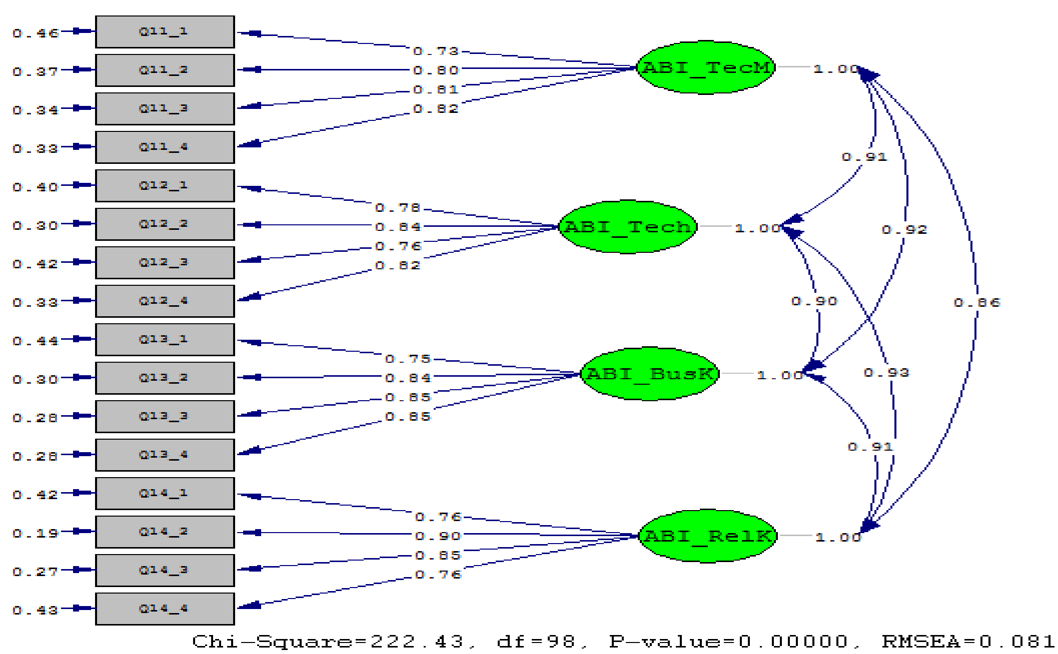

Figure 11. CFA Results for A&BI Talent Capability

Table 21. Fit Indices for Model 2

		RMSEA						
Model	**SRMR**	**LB**	**Estimate**	**UB**	**CFI**	χ^2	***df***	***p***
2	.038	0.067	0.081	0.095	0.985	222.43	98	0.00

Where No. of obs. → 194; SRMR → Standardized Root Mean Square Residual; LB → Lower Bound of 90% confidence interval; UB → Upper Bound of 90% confidence interval; CFI → Comparative Fit Index; χ^2 → Chi square estimate; *df* → degree of freedom; and *p* → *P*-value.

From the summary of the results presented above, it can be concluded that Model 1's chi-square test is significant. This implies that there is significant difference between the model's implied and observed covariance matrices (χ^2 = 222.43, df=98, p<0.00).

Also, RMSEA value was estimated to be 0.081 based on a 90% confidence interval with lower and upper bound ranging between 0.067 and 0.095 respectively. Comparing the estimated RMSEA to the ideal critical value of 0.05, it can be concluded Model 2 does not fit the data well enough because the model's estimated RMSEA together with its corresponding confidence interval bound are greater than the theoretically acceptable threshold (Kline 2010).

However, the model's SRMR value, which is estimated at 0.038, was found to be less than generally acceptable value of 0.08 according to Kline's (2010) text. This result implies that the model fits the data well since its correlation residual (0.038) falls below the acceptable threshold value (0.08).

Moreover, the model's CFI value (0.985) turns out to be greater than theoretically acceptable cutoff value (0.95) as suggested by Kline (2010). The implication of this result, however, is that the model fits the data very well because the greater the better.

In summary, because the model's SRMR, CFI and Chi-square results provide strong proof of good model-to-data fit, and because RMSEA value also suggest fairly good fit, it can be concluded that the overall fit of the model is good.

Table 22. Maximum Likelihood Estimates for a Recursive Path of Model 2

Path	Unstandardized	SE	Standardized	t-value
ABI_TecM → Q11_1	0.953**	0.082	0.733	11.606
ABI_ TecM → Q11_2	0.938 **	0.072	0.796	13.070
ABI_TecM → Q11_3	0.990 **	0.074	0.811	13.437
ABI_TecM → Q11_4	1.037 **	0.076	0.819	13.637
ABI_Tech → Q12_1	1.021**	0.081	0.776	12.629
ABI_Tech → Q12_2	1.032 **	0.073	0.839	14.215
ABI_Tech → Q12_3	0.964 **	0.078	0.762	12.316
ABI_Tech → Q12_4	1.059 **	0.077	0.820	13.715
ABI_BusK → Q13_1	0.888 **	0.074	0.746	11.957
ABI_BusK → Q13_2	1.062 **	0.075	0.839	14.252
ABI_BusK → Q13_3	1.099 **	0.076	0.848	14.494
ABI_BusK → Q13_4	1.117 **	0.117	0.851	14.562
ABI_RelK → Q14_1	0.981 **	0.080	0.759	12.274
ABI_RelK → Q14_2	1.141 **	0.071	0.899	15.958
ABI_RelK → Q14_3	1.216 **	0.083	0.855	14.685
ABI_RelK → Q14_4	1.032**	0.084	0.758	12.242

** $p < 0.001$

4.6.5 A&BI Technology Capability

Below is summary of the CFA results for analytics & business intelligence technology capability.

Table 23. Covariance Matrix for A&BI Technology Capability

	Q15_1	Q15_2	Q15_3	Q15_4	Q16_1	Q16_2	Q16_3	Q16_4	Q17_1	Q17_2	Q17_3	Q17_4	Q18_1	Q18_2	Q18_3	Q18_4
Q15_1	2.207															
Q15_2	1.017	1.917														
Q15_3	1.185	1.289	1.834													
Q15_4	1.365	1.128	1.218	2.358												
Q16_1	1.196	0.914	0.948	1.011	2.101											
Q16_2	1.135	0.961	1.208	1.367	1.342	2.202										
Q16_3	1.078	1.252	1.217	1.208	1.093	1.347	2.005									
Q16_4	1.200	0.983	1.060	1.087	0.952	1.172	1.196	1.969								
Q17_1	1.462	0.935	1.129	1.429	1.254	1.310	1.203	1.270	2.319							
Q17_2	1.210	0.779	0.849	1.322	0.898	1.159	1.022	1.106	1.452	2.420						
Q17_3	1.244	0.753	0.871	1.205	0.858	1.098	0.938	1.120	1.427	1.717	2.113					
Q17_4	1.061	0.755	0.765	1.158	1.054	1.068	0.999	0.904	1.301	1.373	1.278	1.809				
Q18_1	1.153	0.987	1.040	0.956	1.017	1.141	0.999	0.870	1.161	0.931	0.957	1.009	1.899			
Q18_2	0.941	0.740	0.969	1.057	0.586	1.177	0.807	0.764	1.072	1.144	1.083	1.014	1.263	2.207		
Q18_3	1.338	0.958	1.200	1.002	1.079	1.222	1.006	1.139	1.520	1.389	1.345	1.075	1.270	1.392	2.621	
Q18_4	1.290	1.094	1.132	1.178	1.126	1.280	1.187	1.148	1.397	1.260	1.222	1.167	1.258	1.443	1.740	2.129

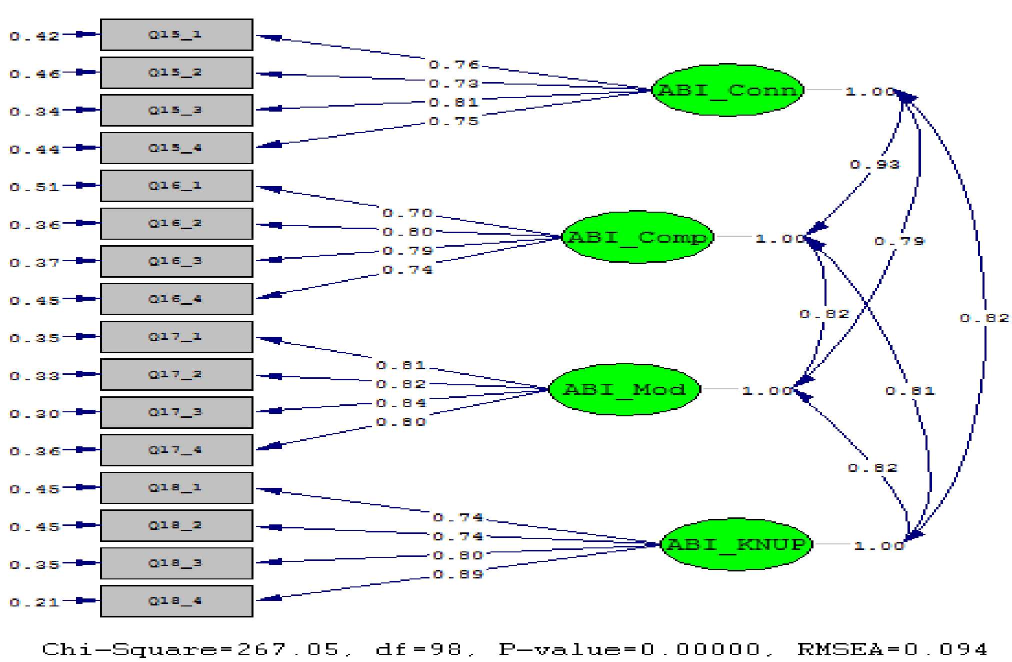

Figure 12. CFA Results for A&BI Technology Capability

Table 24. Fit Indices for Model 3

		RMSEA						
Model	**SRMR**	**LB**	**Estimate**	**UB**	**CFI**	χ^2	***df***	***p***
3	.054	0.081	0.094	0.108	0.974	267.05	98	0.00

Where No. of obs. → 194; SRMR → Standardized Root Mean Square Residual; LB → Lower Bound of 90% confidence interval; UB → Upper Bound of 90% confidence interval; CFI → Comparative Fit Index; χ^2 → Chi square estimate; *df* → degree of freedom; and *p* → *P*-value.

From the summary of the results presented above, it can be concluded that Model 1's chi-square test is significant. This implies that there is significant difference between the model's implied and observed covariance matrices (χ^2 = 267.05, *df*=98, *p*<0.00).

Also, RMSEA value was estimated to be 0.094 based on a 90% confidence interval with lower and upper bound ranging between 0.081 and 0.108 respectively. Comparing the estimated RMSEA to the ideal critical value of 0.05, it can be concluded Model 3 does not fit the data well enough because the model's estimated RMSEA together with its corresponding confidence interval bound are greater than the theoretically acceptable threshold (Kline 2010).

However, the model's SRMR value, which is estimated at 0.054, was found to be less than generally acceptable value of 0.08 according to Kline's (2010) text. This result implies that the model fits the data well since its correlation residual (0.054) falls below the acceptable threshold value (0.08).

Moreover, the model's CFI value (0.974) turns out to be greater than theoretically acceptable cutoff value (0.95) as suggested by Kline (2010). The implication of this result, however, is that the model fits the data very well because the greater the better.

In summary, because the model's SRMR, CFI and Chi-square results provide strong proof of good model-to-data fit, and because RMSEA value also suggest fairly good fit, it can be concluded that the overall fit of the model is good.

Table 25. Maximum Likelihood Estimates for a Recursive Path of Model 3

Path	Unstandardized	SE	Standardized	t-value
ABI_Conn → Q15_1	1.127**	0.093	0.759	12.077
ABI_Conn → Q15_2	1.014**	0.088	0.732	11.494
ABI_Conn → Q15_3	1.101**	0.082	0.813	13.344
ABI_Conn → Q15_4	1.152**	0.097	0.750	11.881
ABI_Comp → Q16_1	1.011**	0.094	0.698	10.767
ABI_Comp → Q16_2	1.188**	0.091	0.801	13.067
ABI_Comp → Q16_3	1.123**	0.087	0.793	12.889
ABI_Comp → Q16_4	1.039**	0.089	0.740	11.674
ABI_Mod → Q17_1	1.228**	0.093	0.806	13.238
ABI_Mod → Q17_2	1.271**	0.094	0.817	13.502
ABI_Mod → Q17_3	1.214**	0.087	0.835	13.974
ABI_Mod → Q17_4	1.072**	0.082	0.797	13.012
ABI_KNUP → Q18_1	1.026**	0.087	0.745	11.811
ABI_KNUP → Q18_2	1.102**	0.094	0.742	11.743
ABI_KNUP → Q18_3	1.303**	0.099	0.805	13.214
ABI_KNUP → Q18_4	1.296**	0.084	0.888	15.396

** $p < 0.001$

4.6.6 A&BI and Organizational Business Alignment

Below is a summary of the CFA results for analytics & business intelligence and organizational business alignment.

Table 26. Covariance Matrix for A&BI and Organizational Business Alignment

	Q19_1	Q19_2	Q19_3	Q19_4
Q19_1	1.534			
Q19_2	1.068	1.687		
Q19_3	1.054	1.196	1.790	
Q19_4	1.049	0.998	1.186	2.046

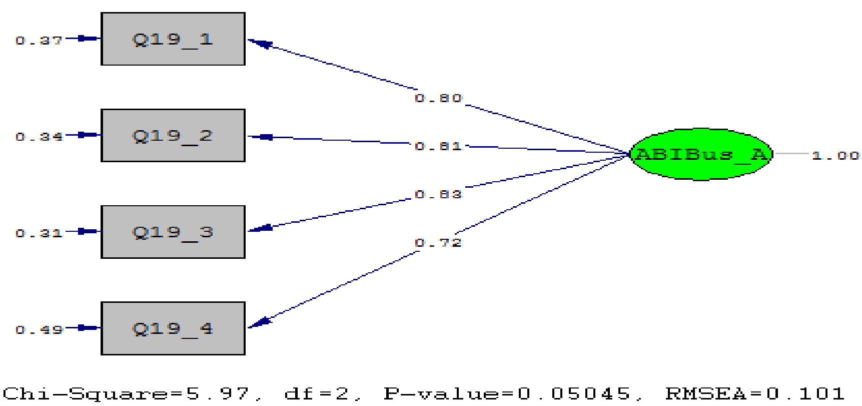

Figure 13. CFA Results for Organizational Business Alignment

Table 27. Fit Indices for Model 4

		RMSEA						
Model	**SRMR**	**LB**	**Estimate**	**UB**	**CFI**	χ^2	*df*	*p*
4	.021	0.000	0.101	0.199	0.991	5.97	2	0.05

Where No. of obs. → 194; SRMR → Standardized Root Mean Square Residual; LB → Lower Bound of 90% confidence interval; UB → Upper Bound of 90% confidence interval; CFI → Comparative Fit Index; χ^2 → Chi square estimate; *df* → degree of freedom; and *p* → *P*-value.

From the summary of the results presented above, it can be concluded that Model 4's chi-square test is significant. This implies that there is significant difference between the model's implied and observed covariance matrices (χ^2 = 5.97, *df*=2, *p*<0.05).

RMSEA value was estimated to be 0.101 based on a 90% confidence interval with lower and upper bound ranging between 0.000 and 0.199 respectively. Comparing the estimated RMSEA to the ideal critical value of 0.05, it can be concluded Model 4 does not fit the data well enough because the model's estimated RMSEA together with its corresponding confidence interval bound are greater than the theoretically acceptable threshold (Kline 2010).

However, the model's SRMR value, which is estimated at 0.021, was found to be less than generally acceptable value of 0.08 according to Kline's (2010) text. This implies that the model fits the data well since its correlation residual (0.021) falls below the acceptable threshold value (0.08).

Moreover, the model's CFI value (0.991) turns out to be greater than theoretically acceptable cutoff value (0.95) as suggested by Kline (2010). The implication of this result, however, is that the model fits the data very well because the greater the better.

In summary, because the model's SRMR, CFI and Chi-square results provide strong proof of good model-to-data fit, and because RMSEA value also suggest fairly good fit, it can be concluded that the overall fit of the model is good.

Table 28. Maximum Likelihood Estimates for a Recursive Path of Model 4

Path	Unstandardized	SE	Standardized	t-value
ABIBus_Al → Q19_1	0.985 **	0.078	0.795	12.644
ABIBus_Al → Q19_2	1.056 **	0.081	0.813	13.035
ABIBus_Al → Q19_3	1.115 **	0.083	0.833	13.512
ABIBus_Al → Q19_4	1.025 **	0.094	0.717	10.947

** $p < 0.001$

4.6.7 Discriminant Validity Tests

Discriminant validity was further assessed in CFA through chi-square (χ^2) tests between constrained model that sets the correlation of the three independent constructs to 1 and an unconstrained model that frees the correlation (Segars and Grover 1998). A significant χ^2 difference suggests that the unconstrained model is a better fit than the constrained model.

I also performed comparative analysis of the second-order factor model with alternative first-order constructs (Segars and Grover 1998, pp. 152-156). Specifically, I tested three models: (i) Model 1: a one-factor model that all the items of only one of the second-order construct load unto; (ii) Model 2: a two-factor model that all the items of two of the second-order construct load unto; and (iii) Model 3: a three-factor model that all the items of three of the second-order construct load unto. The reason for performing this comparative analysis is to be able to verify my theoretical argument driving this study that A&BI capability is best modeled as having three sub-dimensions or sub-constructs. Below is a summary of the results for each of the three different models' (Figures 14-16) tests that was performed.

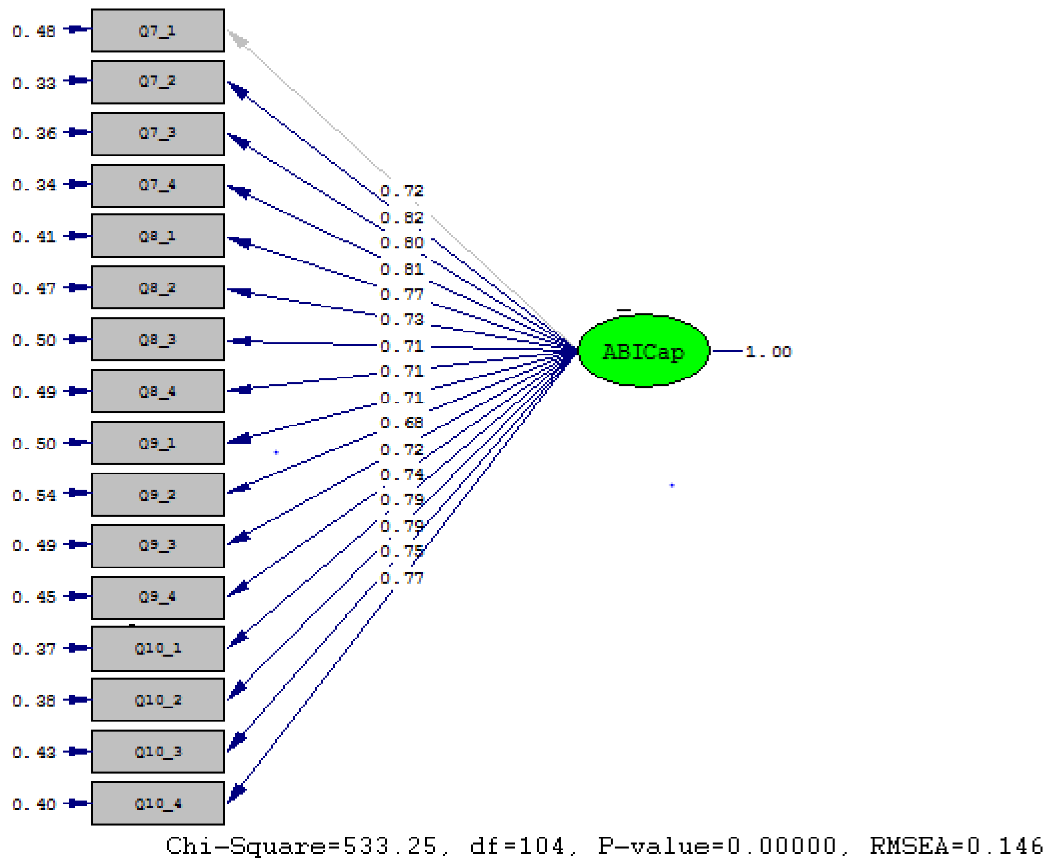

Figure 14. Model 1 (A&BI Capability as a One-Factor Model)

Table 29. Goodness of Fit Statistics for the One-Factor Model

Degrees of Freedom for (C1)-(C2)	104
Maximum Likelihood Ratio Chi-Square (C1)	533.248(P = 0.0000)
Browne's (1984) ADF Chi-Square (C2_NT)	640.214 (P = 0.0000)
Estimated Non-centrality Parameter (NCP)	429.248
90 Percent Confidence Interval for NCP	(360.800 ; 505.216)
Minimum Fit Function Value	2.749
Population Discrepancy Function Value (F0)	2.213
90 Percent Confidence Interval for F0	(1.860 ; 2.604)
Root Mean Square Error of Approximation (RMSEA)	0.146
90 Percent Confidence Interval for RMSEA	(0.134 ; 0.158)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.000

Expected Cross-Validation Index (ECVI)	3.079
90 Percent Confidence Interval for ECVI	(2.726 ; 3.470)
ECVI for Saturated Model	1.402
ECVI for Independence Model	39.271
Chi-Square for Independence Model (120 df)	7586.649
Normed Fit Index (NFI)	0.929
Non-Normed Fit Index (NNFI)	0.933
Parsimony Normed Fit Index (PNFI)	0.805
Comparative Fit Index (CFI)	0.942
Incremental Fit Index (IFI)	0.942
Relative Fit Index (RFI)	0.918
Critical N (CN)	51.839
Root Mean Square Residual (RMR)	0.136
Standardized RMR	0.069
Goodness of Fit Index (GFI)	0.708
Adjusted Goodness of Fit Index (AGFI)	0.618
Parsimony Goodness of Fit Index (PGFI)	0.541

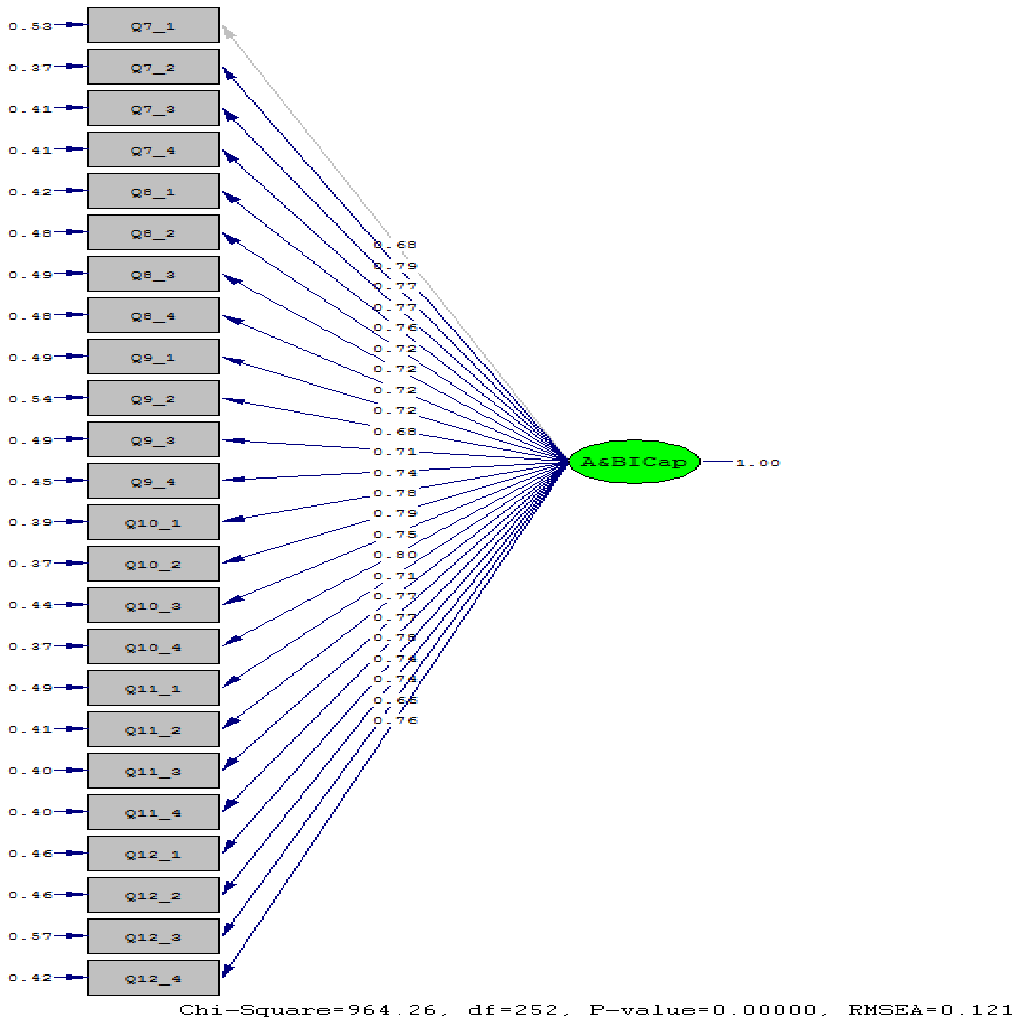

Figure 15. Model 2 (A&BI Capability as a Two-Factor Model)

Table 30. Goodness of Fit Statistics for the Two-Factor Model

Degrees of Freedom for (C1)-(C2)	252
Maximum Likelihood Ratio Chi-Square (C1)	964.263 (P = 0.0000)
Browne's (1984) ADF Chi-Square (C2_NT)	1078.035 (P = 0.0000)
Estimated Non-centrality Parameter (NCP)	712.263
90 Percent Confidence Interval for NCP	(620.761 ; 811.324)
Minimum Fit Function Value	4.970
Population Discrepancy Function Value (F0)	3.671
90 Percent Confidence Interval for F0	(3.200 ; 4.182)
Root Mean Square Error of Approximation (RMSEA)	0.121

90 Percent Confidence Interval for RMSEA	(0.113 ; 0.129)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.000
Expected Cross-Validation Index (ECVI)	5.465
90 Percent Confidence Interval for ECVI	(4.994 ; 5.976)
ECVI for Saturated Model	3.093
ECVI for Independence Model	85.778
Chi-Square for Independence Model (276 df)	16593.024
Normed Fit Index (NFI)	0.942
Non-Normed Fit Index (NNFI)	0.952
Parsimony Normed Fit Index (PNFI)	0.860
Comparative Fit Index (CFI)	0.956
Incremental Fit Index (IFI)	0.956
Relative Fit Index (RFI)	0.936
Critical N (CN)	62.477
Root Mean Square Residual (RMR)	0.115
Standardized RMR	0.0619
Goodness of Fit Index (GFI)	0.683
Adjusted Goodness of Fit Index (AGFI)	0.623
Parsimony Goodness of Fit Index (PGFI)	0.574

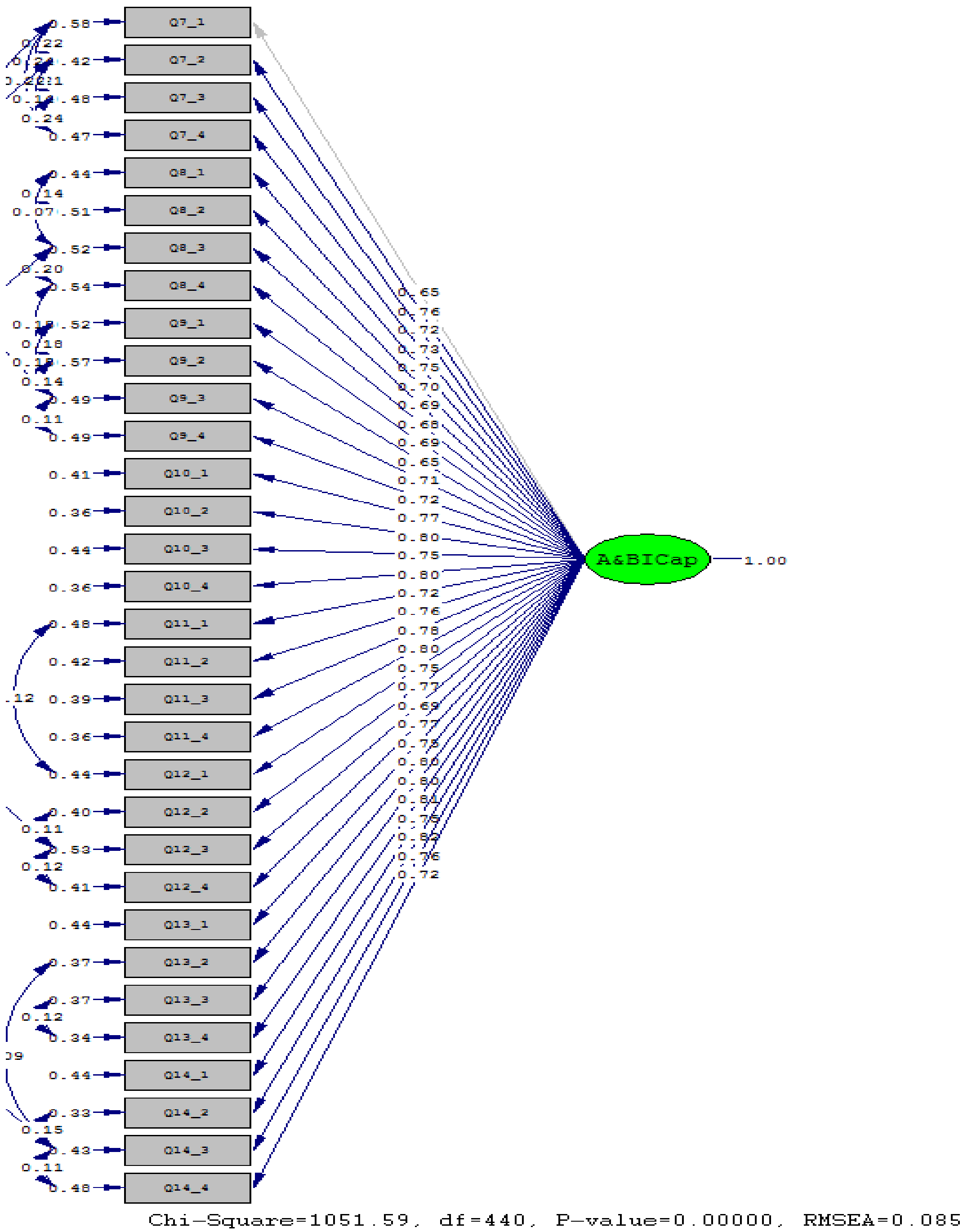

Figure 16. Model 3 (A&BI Capability as a Three-Factor Model)

Table 31. Goodness of Fit Statistics for the Three-Factor Model

Degrees of Freedom for (C1)-(C2)	440
Maximum Likelihood Ratio Chi-Square (C1)	1051.589(P = 0.0000)
Browne's (1984) ADF Chi-Square (C2_NT)	1004.351(P = 0.0000)
Estimated Non-centrality Parameter (NCP)	611.589
90 Percent Confidence Interval for NCP	(520.534 ; 710.333)
Minimum Fit Function Value	5.421
Population Discrepancy Function Value (F0)	3.153
90 Percent Confidence Interval for F0	(2.683 ; 3.662)
Root Mean Square Error of Approximation (RMSEA)	0.0846
90 Percent Confidence Interval for RMSEA	(0.0781 ; 0.0912)
P-Value for Test of Close Fit (RMSEA < 0.05)	0.000
Expected Cross-Validation Index (ECVI)	6.328
90 Percent Confidence Interval for ECVI	(5.858 ; 6.837)
ECVI for Saturated Model	5.443
ECVI for Independence Model	157.110
Chi-Square for Independence Model (496 df)	30415.401
Normed Fit Index (NFI)	0.965
Non-Normed Fit Index (NNFI)	0.977
Parsimony Normed Fit Index (PNFI)	0.856
Comparative Fit Index (CFI)	0.979
Incremental Fit Index (IFI)	0.979
Relative Fit Index (RFI)	0.961
Critical N (CN)	94.957
Root Mean Square Residual (RMR)	0.085
Standardized RMR	0.048
Goodness of Fit Index (GFI)	0.756
Adjusted Goodness of Fit Index (AGFI)	0.707
Parsimony Goodness of Fit Index (PGFI)	0.630

Table 29 below presents summary results of the comparative factor analysis and alternative measurement models specification.

Table 32. Comparative Model Indices

Model	χ^2(df)	Normed χ^2	GFI	CFI	NNFI	SRMR
Recommended Values		***≤ 3.0***	***≥ 0.90***	***≥ 0.95***	***≥ 0.95***	***≤ 0.08***
Model 1 (Single factor)	533.248(104)	5.127	0.708	0.942	0.933	0.0694
Model 2 (2 uncorrelated factors)	964.263(252)	3.826	0.683	0.956	0.952	0.0619
Model 3 (3 correlated factors)	1051.589(440)	2.389	0.756	0.979	0.977	0.0477

Where χ^2 → Chi square; Normed χ^2 →(χ^2 /df); GFI → Goodness of Fit Index; CFI → Comparative Fit Index; NNFI → Non-Normed Fit Index; and SRMR → Standardized Root Mean Square Residual.

From the comparative CFA measurement models specification results presented in Table 29 above, it can be concluded that the overall fit of Model 3 is the best compared to Models 2 and 1. Thus, Model 3 turns out to be the best fit model due to its relatively lowest normed chi-square value (2.389) as well as standardized root mean square residual value (0.04). Moreover, Model 3 relatively outperformed Models 1 and 2 with respect to its highest goodness of fit index value (0.756), highest comparative fit index value (0.979) and highest non-normed fit index value (0.977).

In summary, the overall model fit indices and the significant factor loadings, as illustrated in Figure 11, further support the main argument for my measurement model specification, thereby providing a strong confirmation and support for discriminant validity among the three sub-constructs of A&BI.

Together, these results provide evidence that the third-order model of (A&BI) capability is not unidimensional as has traditionally been theorized in the literature. Rather, A&BI capability is a good fit model conceptually and empirically when modeled as multi-dimensional construct with three second-order sub-constructs (Figure 17).

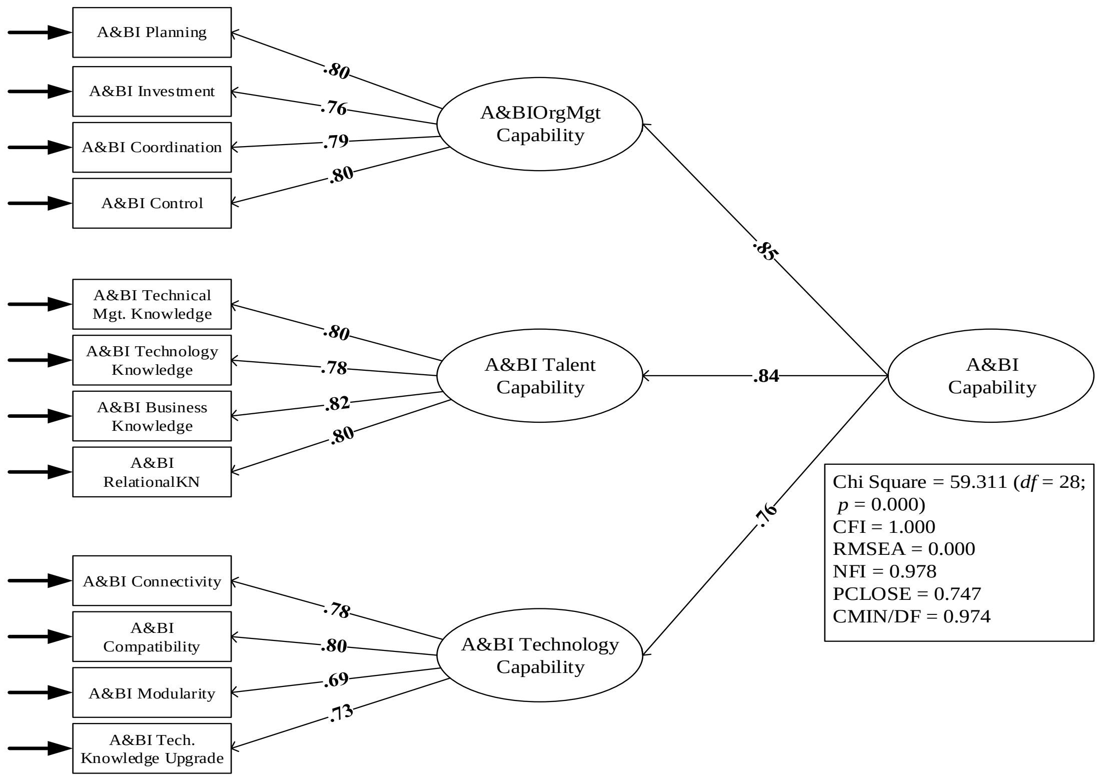

Figure 17. Third-Order Model of IT Capability Results

4.6.8 Tests of Common Method Bias

I also further assessed the measures to ensure that the effect of common method bias is minimized. First, multiple respondents (IT employees and business executives in healthcare organizations) were used for data collection to minimized the potential effect of common method bias. Then, both the independent variables and dependent variable (healthcare organizations performance improvement) were measured by asking IT employees and management executives of healthcare organizations to complete the survey. Second, I also conducted Harman's post hoc single-factor analysis to examine for method bias in the data. If common method variance is a common issue, a factor analysis would generate a single factor accounting for most of the variance (Podsakoff, MacKenzie, Lee, and Podsakoff 2003). Third, CFA was performed to test a single factor model (Kearns and Sabherwal 2007). The model exhibited a poor fit with $\chi^2 = 533.248$ (df = 104); Normed $\chi^2 = 5.127$; SRMR = 0.0694; RMSEA = 0.146; CFI = 0.942; NNFI = 0.933; and GFI = 0.708. These findings from the diagnostic analyses indicate that common method bias is unlikely to be an issue with the data.

I also performed additional cross-validation tests on a subset of the sample for which objective demographics were available. This results provides further evidence for the validity of the survey data.

4.7 Hypothesis Tests (Structural Analysis)

Regression analysis using Maximum Likelihood estimation approach was used to test the research hypotheses. The multi-item measures were initially transformed into summated scales. In order to reduce any potential problems of multicollinearity, study variables were first mean centered prior to forming the multiplicative product term (Cohen, Cohen, West, and Aiken. 2003). I also mean centered all control variables (excerpt industry type and technology use/reliance) to ensure easy interpretation of the coefficients. I tested four different models: (i) Model 1: main effects of path diagram and control variables; (ii) Model 2: effects of only control variables; (iii) Model 3: main effects of only path diagram without controls; and (iv) Model 4: full model effects with interaction terms and controls Figure 15 and Table 30 present a summary of the path diagram results.

As shown in Table 30 and Figure 24 below, the results (Model 3) provide strong support for H1 and H2 as indicated by significant positive coefficients of analytics and business intelligence (A&BI) capability on healthcare organizational performance improvement (β=0.43; ρ<0.001) and the alignment between A&BI and BSA on organizational performance improvement (β=0.61; ρ<0.001) over and above the effect of all control variables combined.

Table 33. Results of Maximum Likelihood Estimate Regression Analysis of Research Hypotheses

Variable	Model 1 Controls	Model 2 Main Effect without Controls	Model 3 Main Effect with Controls	Model 4 Full Model with Interaction & Controls
Intercept	29.052***	9.947***	9.448***	7.923***
Control1: *firm size*	0.415		0.272	0.244
Control2: *firm age*	-0.058		-0.222	-0.195
Control3: *Industry type*	0.514		0.560	0.301
Control4: *Technology use*	0.254		-0.506	-0.549
A&BI Capability		0.454***	0.430***	0.451***
A&BI-BSA		0.581***	0.606***	0.657***
A&BI Capability x A&BI-BSA				0.616***
R^2	0.02	0.52	0.54	0.55
F	0.54	12.87**	103.89**	74.26**

Note: ***p < 0.001; **p < 0.01; All variables are mean centered for moderation analyses.

I further performed additional comparative analysis (Model 2) to further investigate the relationship among A&BI capability, A&BI-BSA and healthcare organizations performance improvement. Thus, I regressed A&BI capability on organizational performance improvement, controlling for the effects firm size, firm age, industry type and technology use. The results show a significant positive effect of A&BI capability on organizational performance improvement (β=0.45; ρ<0.001) over and above all the four variables. This suggests that higher analytics and business intelligence capability developed within healthcare organizations leads to superior improvement in general healthcare organizational performance.

Similarly, I also regressed the alignment between A&BI capability and organization existing business strategies (A&BI-BSA) on performance improvement, controlling for the effects of all the four control variables. The results show a significant positive effect of A&BI-BSA on performance improvement (β=0.58; ρ=0.001) over and above all the four control variables. This suggests that better alignment between current and emerging analytics and business intelligence techniques, process, and capabilities is key to improving superior healthcare organizational performance. Thus, the positive main effect of A&BI capability and the alignment between this capability and existing business routines or processes in healthcare organizations is strong indicative of healthcare organizations that are on track with of ensuring better alignment of the emerging A&BI technologies and process with organizational overall business objectives and strategies. Such organizations are likely to be doing a good job by better managing their IT investment and direct their spending on the appropriate A&BI resources such as, for example, investing in upgrading their hardware, software, and networks that help to increase productivity and efficiency.

Moreover, the results (Model 4) also show support for H3, which is, A&BI-BSA has a significant positive moderating effect on the relationship between A&BI capability and organizational performance improvement (β=0.62; ρ=0.001). This effect is represented in Figure 15 by the interaction between A&BI capability construct and the

A&BI-BSA construct. Note that the main effects of A&BI capability and A&BI-BSA remain significant after entering the interaction terms (Model 4). This significant positive moderation effect indicates that the relationship between A&BI capability and organizational performance improvement is positively improved by ensuring better A&BI-BSA strategy.

In addition to these findings from the hypotheses tests, several interesting findings are also apparent from the test of control variables as elaborated in Model 1 analysis. The control variables were altogether not found to be significant in general. Also, each individual control was not found to be significant as each of their t-statistics values were greater than the acceptable cutoff point (1.98) and their *p*-values also greater than the acceptable threshold (0.05) as shown in Table 30 above. Whiles firm size (*control1*), industry type (*control3*) and technology use (*control4*) were found to have positive non-significant impact on organizational performance improvement, the impact of firm age (*control2*) was found to have a negative non-significant impact (β=-0.06; ρ=0.896). This finding indicates that there is no significant difference between older and relatively younger firms when it comes to the development of A&BI capability to improve organizational performance.

In the following section I present the detail results of the analysis of testing different alternative models to help better investigate the impact of A&BI capability and A&BI-BSA on organizational performance improvement.

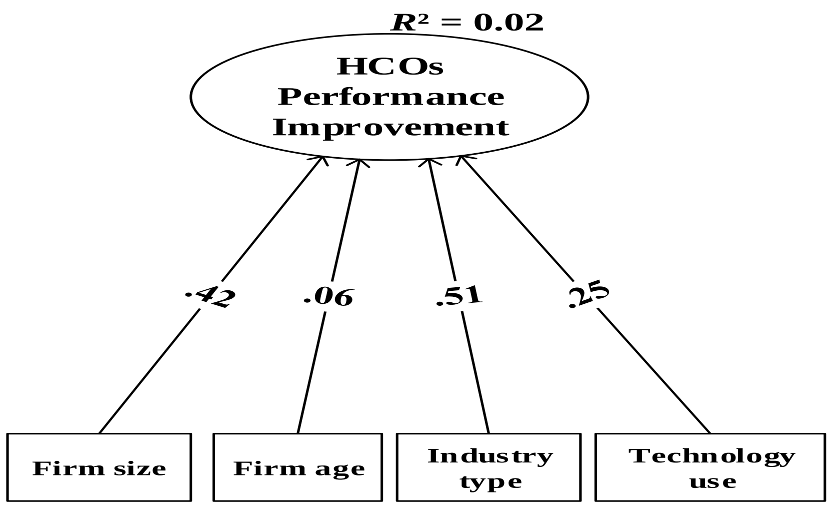

Figure 18. Results of Structural Analysis of the Effect of Controls (Model 1)

Table 34. Maximum Likelihood Estimates (Regression Weights)

	Estimate	S.E.	t-statistics	*p*-value
Intercept	29.052	3.277	8.865	***
Firm size → OrgPerfImprove	.415	.315	1.318	.187
Firm age → OrgPerfImprove	-.058	.438	-.131	.896
Industry type → OrgPerfImprove	.514	1.185	.434	.664
Technology use → OrgPerfImprove	.254	1.061	.239	.811

Table 35. Variances

	Estimate	S.E.	C.R.	P
Firm size	4.773	.698	6.839	***
Firm age	2.664	.390	6.838	***
Industry type	.290	.042	6.838	***
Technology use	.378	.055	6.838	***

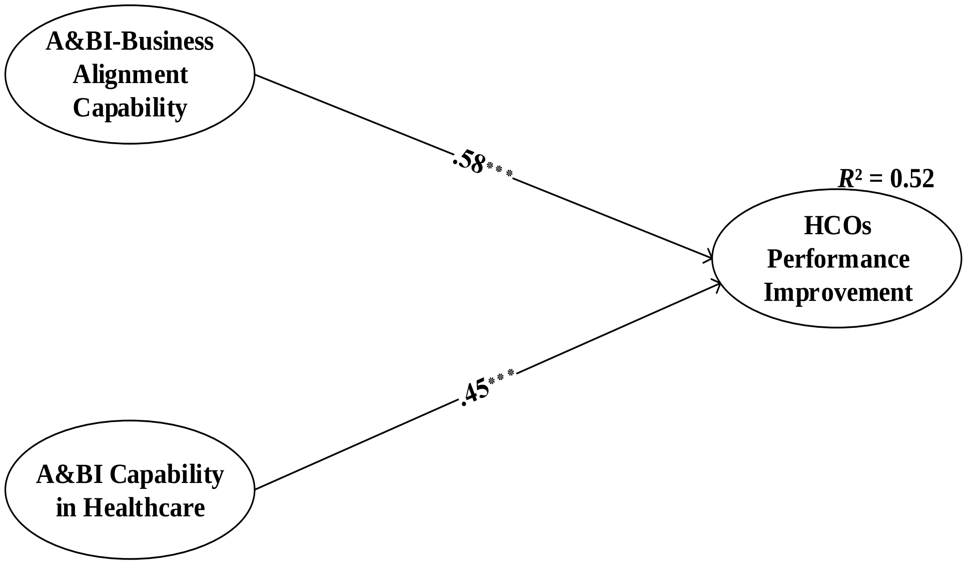

Figure 19. Results of Structural Analysis of Main Effect without Controls (Model 2)

Table 36. Maximum Likelihood Estimates (Regression Weights)

	Estimate	S.E.	t-statistics	P
Intercepts	9.947	1.551	6.415	***
ABIBusAlign → OrgPerfImprove	.581	.105	5.554	***
ABICap → OrgPerfImprove	.454	.105	4.343	***

Table 37. Variances

	Estimate	S.E.	C.R.	P
ABIBusAlign	20.054	2.041	9.823	***
ABICap	20.097	2.046	9.823	***

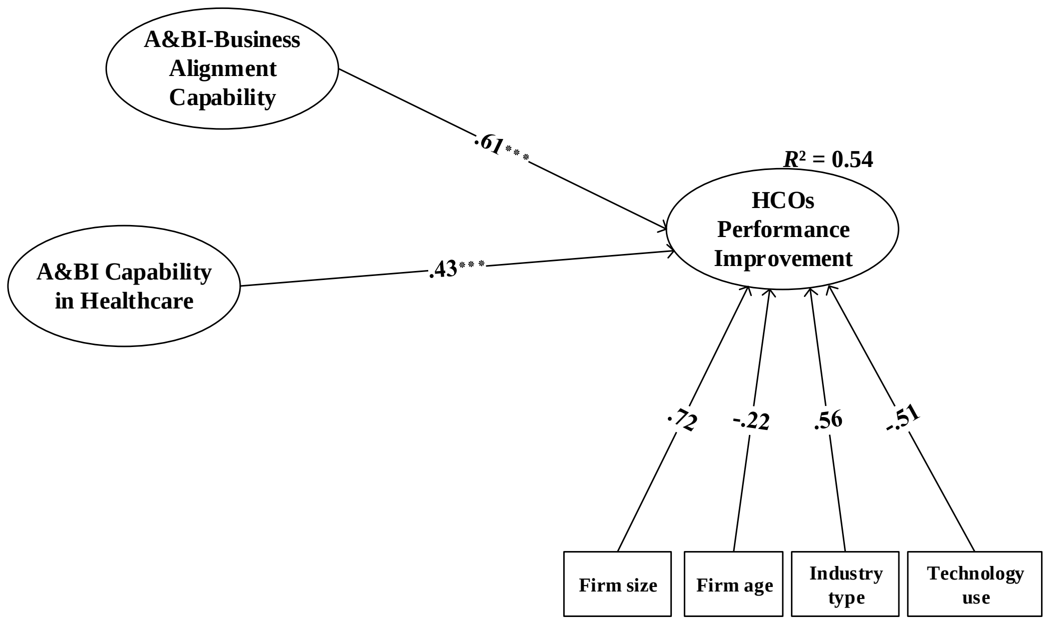

Figure 20. Results of Structural Analysis of Main Effect of Constructs & Controls (Model 3)

Table 38. Results of Maximum Likelihood Estimate (Regression Weights)

	Path Coefficients (Estimates)	**S.E.**	**t-statistics**	***p-value***
Intercepts	9.448	2.724	3.468	***
ABIBusAlign → OrgPerfImprove	.606	.104	5.835	***
ABICap → OrgPerfImprove	.430	.104	4.144	***
Firm size → OrgPerfImprove	.272	.218	1.250	.211
Firm age → OrgPerfImprove	-.222	.302	-.734	.463
Industry type → OrgPerfImprove	.560	.816	.686	.493
Technology use → OrgPerfImprove	-.506	.730	-.693	.488

Table 39. Variances

	Estimate	S.E.	t-statistics	*p-value*
ABIBusAlign	20.054	2.041	9.823	***
ABICap	20.097	2.046	9.823	***
Disturbance term	16.981	1.781	9.533	***
Firm size	4.762	.696	6.838	***
Firm age	2.664	.390	6.838	***
Industry type	.289	.042	6.838	***
Technology use	.377	.055	6.838	***

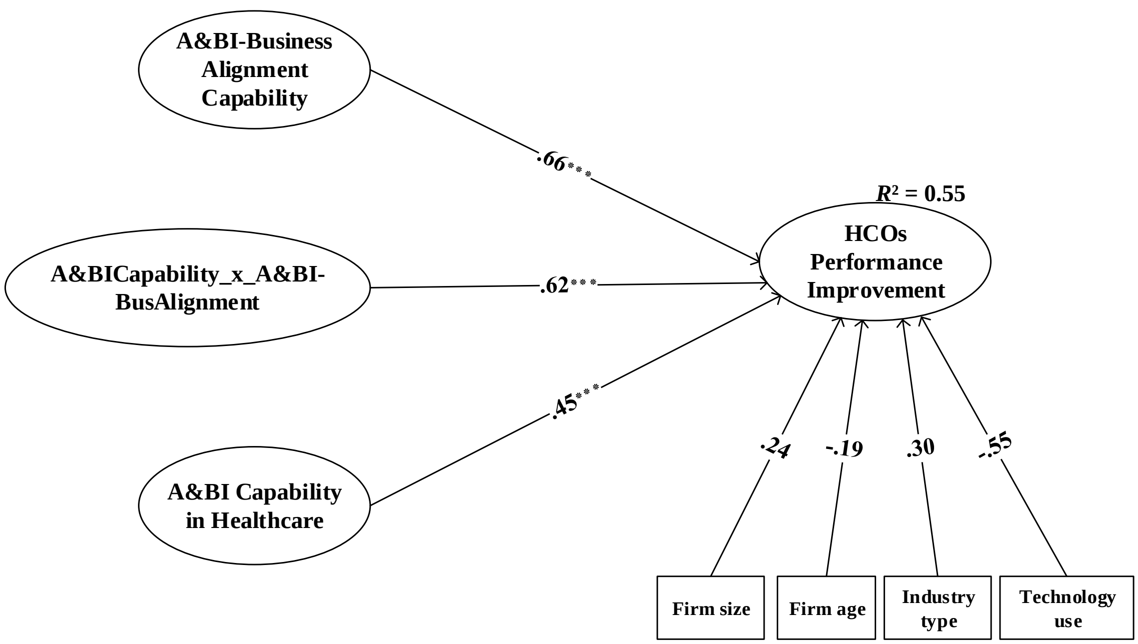

Figure 21. Result of Structural Analysis of Full Model with Interaction Terms and Controls (Model 4)

Table 40. Maximum Likelihood Estimates (Regression Weights)

	Estimate	S.E.	t-statistics	p-value
Intercepts	7.923	2.777	2.853	.004
ABICap → OrgPerfImprove	.451	.102	4.421	***
ABIBusAlign → OrgPerfImprove	.657	.104	6.327	***
ABICap_x_ABIBusAlign → OrgPerfImprove	.616	.226	2.729	.006
Firm size → OrgPerfImprove	.244	.214	1.139	.255
Firm age → OrgPerfImprove	-.195	.297	-.657	.511
Industry type → OrgPerfImprove	.301	.803	.374	.708
Technology use → OrgPerfImprove	-.549	.718	-.766	.444

Table 41. Variances

	Estimate	S.E.	C.R.	P
ABICap	20.097	2.046	9.823	***
ABIBusAlign	20.054	2.041	9.823	***
ABICap_x_ABIBusAlign	1.945	.198	9.823	***
Firm size	4.762	.696	6.838	***
Firm age	2.664	.390	6.838	***
Industry type	.290	.042	6.838	***
Technology use	.377	.055	6.838	***

4.7.1 Moderation Analysis

I performed the moderating effect analysis by multiplying the aggregate measures of A&BI capability and A&BI-BSA constructs to create an interaction/moderating construct and tested the of two existing latent constructs as well as the newly created interaction term on HCOsPerf construct (Figure 22).

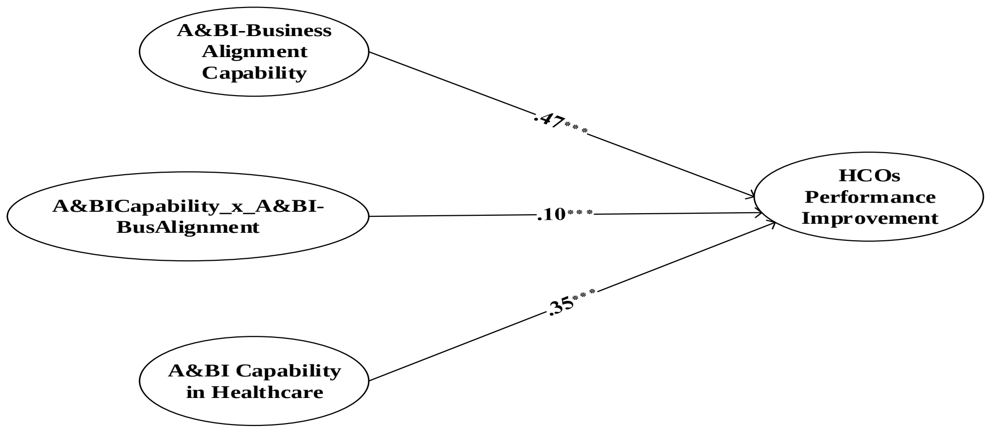

Figure 22. Results of Testing Moderating Effect

From Figure 22 above, it was observed that A&BI-BSA positively moderates the relationship between A&BI capability and healthcare organizations performance improvement. Moreover, as shown in Figure 23 below, it was further observed that at low levels of A&BI-BSA, organizational performance improvement does not change much with the level of A&BI capability. However, at high level of A&BI-BSA, organizational performance improvement is relatively higher and changes significantly with changes of A&BI capability. Figure 23 below is a summary plot of the result from performing the moderating analysis test.

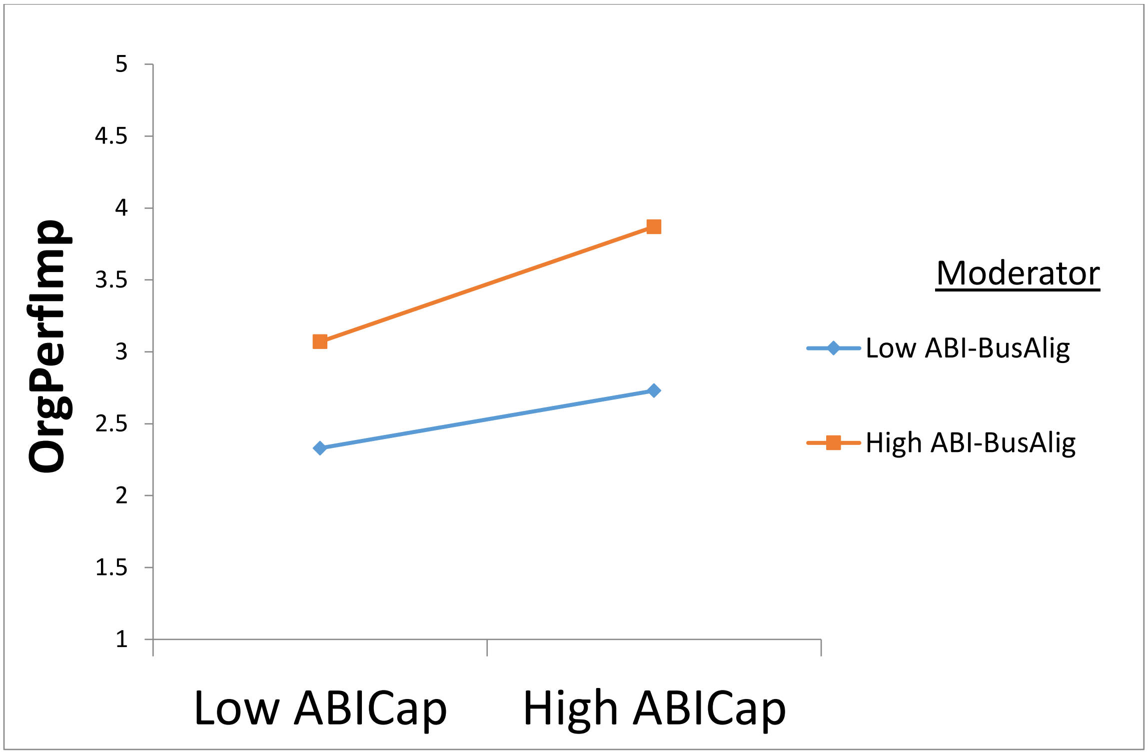

Figure 23. Plot of the Results from Moderating Analysis

4.8 Discussion

This study was set out to address four key research questions:

1. what are the building blocks of A&BI capability in healthcare organizations?

2. how is this A&BI capability developed within HC organizations?

3. what are impacts of this A&BI capability on HC organizations performance?

4. does A&BI-BSA moderate the relationship between A&BI and HCOsPerf?

With regards to the first and second questions, Analytics and Business Intelligence (A&BI) capability was found to exist as a third-order construct which is best conceptualized and measured by three second-order sub-constructs namely: A&BI

organizational management capability (A&BIOrgMgt), A&BI talent capability (A&BITalent), and A&BI technology capability (A&BITech). Of all these three sub-dimension of A&BI capability, A&BIOrgMgt capability emerged as having the strongest associative relationship with A&BI capability, followed by A&BITalent and A&BITech as shown by their confirmatory factor loadings (0.85, 0.84, and 0.76) respectively represented in Figure 11 above.

These findings indicate that managerial support and deep involvement towards the implementation of analytics and business intelligence systems, techniques and process are key to developing a strong A&BI capability from healthcare organizations perspectives. Talent was also found to be equally important priority in developing A&BI capability within healthcare organizations. Technology was found to be the least priority or concerns to developing A&BI capability within healthcare organizations. These findings are consistent with my initial case study findings where majority of study respondents were mostly of the same opinion that managerial involvement as well as lack of talent are the two major drawbacks to the successful development and/or implementation A&BI capability within their organization. Due to privacy and security issues, as well as the sensitive nature of their data, healthcare organizations require strong managerial support and involvement, and people with highly qualified skills and domain knowledge to implement and use a particular technology. For this reason, healthcare organizations are currently behind with regards to the adoption, implementation and use of current and emerging A&BI related technologies that other industries are currently leveraging to drive performance. Their main concern is not about the implementation of the technology as they are relatively more than capable of purchasing and implementing these technologies. Rather, healthcare organizations would consider all the associated risks that goes with the adoption and implementation of the technology. To mitigate this risk, they would take their time to conduct feasibility study by making sure that they are able to answer some fundamental questions such as: would top-level management buy into the idea of implementing a new technology? what are possible costs/benefits for implementing this technology? do we have the employees with the right talent and skills to utilize and manage this technology? etc. Until such questions are clearly articulated and addressed, healthcare organizations would not implement any new or emerging technology due to their risk-averse attitude. Hence, they always lag behind in the adoption and implementation of emerging technologies needed to drive and enhance their performance.

The study also found strong support for the conceptualization that each of the three sub-dimensions of A&BI capabilities also have four primary sub-constructs that reflectively measures their respective second-order constructs. As shown in Figure 11, their factor loadings (Cronbach Alphas) from a confirmatory factor analysis are all almost above the recommended threshold (0.7), indicating a strong positive association to their respective second-order constructs. Although the study prioritizes the importance of the overall A&BI dimensions in terms of explained variance, it recommends that equal attention should be paid to all the dimensions in order to achieve successful application in healthcare organizations.

With regards to the third question, this study found significant positive effect of A&BI capability on healthcare organizations performance improvement. In addition, I also found a significant positive direct effect of A&BI-BSA on healthcare organizations performance improvement, as well as a significant positive moderation effect of A&BI-BSA on the relationship between A&BI and organizational performance improvement, thus providing a strong answer to the fourth question. Overall, the findings of the structural model confirm that A&BI is a significant predictor of HCOsPerf (explaining 52% of the variance). These findings also confirm A&BI-BSA as a significant moderator or, in other words, the necessary condition for a strong firm performance (HCOsPerf). The interaction model explained about 55% of the variance.

In summary, these findings suggest that healthcare organizations already implementing or considering to implement A&BI-enabled systems and techniques would be better of considering a higher A&BI capability and A&BI-BSA as key antecedents that strongly influence their organization's overall performance. Figure 24 and Table 39 are summary of the results of the hypotheses tests and measurement model.

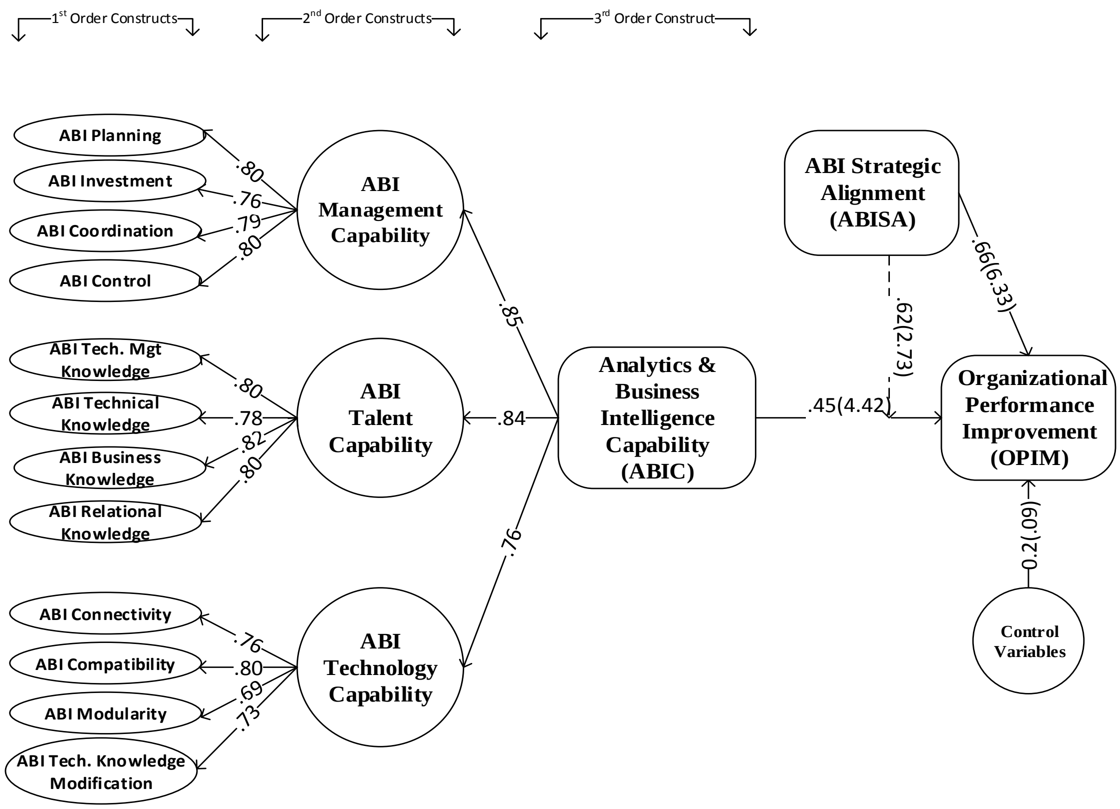

Figure 24. Summary of the Results of Measurement and Structural Model

Table 42. Summary of Hypotheses and Results

Hypothesis	Type of Effect	Relationship	Predicted Sign	Results
H1	Direct effects	A&BI capability → Organizational Performance improvement	+	Supported
H2	Direct effects	A&BI capability and Organizational business strategic alignment → Organizational performance improvement	+	Supported
H3	Moderating effects	A&BI capability x Organizational business strategic alignment → Organizational performance improvement	+	Supported

This study provides initial empirical evidence via a rigorous examination of the relationship between A&BI capability and healthcare organizational performance improvement. I synthesized and theorized the commonly observed but understudied A&BI capability contradictions that this capability is unidimensional. This helped us to extend the enabling role of A&BI to better understand the relationship between A&BI capability and firm performance. By refining the conceptualization and measurement of A&BI capability, I advance both theory and measurement about essential A&BI capabilities and their relationship with firm performance. In a broader sense, such knowledge is fundamental to better understand A&BI business value because A&BI capability is becoming a central concept in modern IT-based value creation (Wang et al. 2016). The advancement in measurement is in line with the recent call for closer attention to auxiliary theory development in research that focus on theoretical conceptualization and measurement model development (Kim et al. 2010).

4.8.1 Theoretical Contribution

This study makes several contributions to A&BI research. First, I conceptualize the multidimensional construct of A&BI capability as a hierarchical third-order level construct that is manifested in three second-order sub-dimensions and captures the commonality among the sub-dimensions. This conceptualization emphasizes the complementarity among the dimensions, that is, the three A&BI capability sub-dimensions together enhance performance improvement in healthcare organizations. The study develops the scale of three primary A&BI capability construct, and 12 sub-constructs and their associated measurement items against the backdrop of capability research in healthcare organizations domain. The findings therefore contribute to answering, “What capabilities (technical and non-technical) should healthcare organizations focus on developing in order to succeed in their current data-rich-but-information-poor environment?” This situation healthcare organizations find themselves in is arguably one of the most interesting questions in the field of analytics, BI and big data research domain today (Phillips-Wren et al., 2015, p. 465). The empirical findings of this study answer this question, and are consistent with the conceptual findings of Kiron et al. (2014) who state that, “an effective analytics culture is built on the backs of more advanced data management processes, technologies and talent.”

Second, despite the paucity of empirical modeling in A&BI research, this study extends this stream by conceptualizing a multi-dimensional A&BI model drawing on the RBV and socio-materialism theories to substantiate the fact that A&BI is a hierarchical multidimensional construct that have a strong significant influence on healthcare organizations performance. This research applies RBV theory as a unifying paradigm for combining other theories (e.g. socio-materialism and IT capability) and presents a parsimonious foundation for multiple theoretical perspectives. Using this foundation, this study provides a hierarchical model for integrating multiple and diverse capabilities into one framework to model their relative and synergistic effects on healthcare organizations performance. Giving the emerging big data analytics research is now fledgling and therefore struggling to better conceptualize and prove the significance of A&BI capability as a source of firm performance, this study specifically addresses this challenge. Thus, this research conceptualizes and empirically validates A&BI capability as a third-order construct or model to capture the variations in organizational performance from healthcare organizational perspective.

Third, by applying the RBV theory and the socio-materialism perspective in conceptualizing A&BI within healthcare context, this study proves its utility in portraying the entanglement phenomenon in A&BI dynamics. Thus, the study's research model has provided evidence of its rigor and power not only in proving structural parsimony but also in explaining theorized interactions which have been manifested at the first-order, second-order and third-order constructs.

Fourth, this study contributes by exploring the dimensions and sub-dimensions of A&BI and providing possible solutions to the challenges of such dimensions.

Lastly, the study adds further theoretical rigor by analyzing and measuring the moderating effect of A&BI-BSA on HCOsPerf. This finding confirms that the fit between capability and strategy can help healthcare organizations to perceive, assess, and act upon their micro and macro environments (Constantiou and Kallinikos 2014). The results on the moderating effect further clarify the conceptual model and extend the theoretical contributions by framing the impact of complex, hierarchical A&BI capability model on firm performance in healthcare context. Overall, the findings of the study help minimize confusions regarding the role of strategic alignment in the RBV theory framework (Teece 2014).

4.8.2 Managerial Contribution

With the ubiquity of healthcare organizations data and the growing need of analytics and business intelligence techniques and capabilities to derive actionable insight from their massive data, this study has important implications for practice. First, the study suggests that A&BI capability is an important enabler of improved performance in healthcare organizations, thus confirming the relationship between high-level A&BI capability and HCOsPerf. Specifically, the results indicate that A&BI capability significantly contributes to the improvement in patient care giving, engagement with patience by enhancing communication, improvement in patient satisfaction, helps in reducing emergency department crowding, enhancing insurance payment and financial claims, etc.

The results also suggest that improvement of overall A&BI capability can be linked with dimensional and sub-dimensional levels. As an example, A&BI management (A&BIMgt) capability could be enhanced by improving the quality of clinical planning, investment, coordination, and control. Similarly, A&BI Talent (A&BITalent) capability could be upgraded by recruiting highly-skilled and experienced employees or through training to achieve better skills and domain knowledge of the workforce. Moreover, A&BI technology (A&BITech) capability could also be improved by enhancing the performance of the A&BI platforms in terms of connectivity, compatibility, and modularity. These linkages in the research model provide managers with an understanding of the antecedents of overall A&BI capability building elements and their relationship with the individual capability dimensions. Indeed, the overall A&BI

capability model development within a data-oriented healthcare organizations has the potential to foster what Kiron and Shockley (2012) call "competitive analytics or analytics that delivers advantage in the marketplace" (p. 59).

Secondly, the findings of this study emphasize not only the importance of A&BI building blocks, but also a strong alignment between A&BI capability and A&BI-BSA needed to achieve performance improvement within healthcare organizations. These findings are consistent with Court (2015) who found that organizations could increase operating margin by 60% as a result of ensuring a tight alignment between analytics efficiency and strategy. Also, prior studies in IT capability research support the importance of capability-strategy alignment by focusing on business process agility (Chen et al. 2014), organizational agility (Lu and Ramamurthy, 2011), and process orientation dynamic capabilities (Kim et al. 2011).

Lastly, the findings of this study have huge practical implications for various healthcare organizations that are currently in the process of developing A&BI capability. For example, by improving A&BI capability and aligning strategy, healthcare organizations managers could better meet customer needs through effective communication; create more effective new care and service delivery strategies that are patient-centric; significantly reduce hospital readmission rate, as well as decrease wait time at the emergency department to avoid overcrowding. According to Wixom et al. (2013), once A&BI and big data related capabilities are established, business value maximized by using practices that drive speed to insight and by making A&BI usage pervasive across the enterprise. Consequently, there is a growing focus on the A&BI-A&BIBSA-HCOPerf link in the A&BI environment within the entire healthcare industry.

4.8.3 Limitations and Future Research Directions

The study has a few limitations that can be extended in the various areas of research. First, the study was conducted using only healthcare organizations as study sample and the main source of data collection. Thus, the scope was limited to exploring A&BI capability building elements and the impact of A&BI capability on performance of only healthcare organizations. It would therefore be interesting to extend this study to other businesses and organizations in various industries, integrating more variables such as business process agility (Chen et al. 2014) and process-oriented dynamic capabilities (Kim et al. 2011) into future studies.

Second, certain important parameters such as privacy and security concerns, the analytics climate, organizational culture, structure, etc. could not be encapsulated into this study due to time and resources constraints. It would therefore be very interesting to investigate the influence of these variables in future research. Thus, future research should extend this study and examine how other elements interacts with A&BI capability in enabling organizational performance improvement.

Third, this study used a 7-point Likert scale to measure all the items, which has the potential to introduce the so-called ‘acquiescence bias’ (Chin et al. 2008). Consequently, future research could consider extending the scale to a 9-point scale of fast form items with the two-anchor points ranging between -4 and +4 as recommended by Chin et al. (2008).

Fourth, future research should explore the various mechanisms for implementing superior A&BI capability to achieve organizational performance improvement. For example, healthcare organizations may go through different pathways to build A&BI capability for performance improvement over time (Lu and Ramamurthy 2011). Likewise, healthcare organizations can adopt different technology, skilled expertise and organizational support to develop and implement A&BI capability. For example, firms could use different mechanisms, such as built-in capabilities, globally consistent integrated data, third party add-on systems, or vendor-provided patches in enterprise systems, to enable firm performance (Goodhue, Chen, Boudreau, Davis, and Cochran. 2009). This study's findings can shed useful light in a future study examining the appropriate use of various elements in developing A&BI capability.

Lastly, this study does not evaluate unobserved heterogeneity in the structural equation model (SEM). As such, future studies could attempt to incorporate the evaluation of the unobserved heterogeneity into its data analysis strategy.

4.9 Conclusion

This research develops and validates a theory of A&BI strategy that shows how healthcare organizations can build a strong A&BI capability and leverage this capability to improve their overall performance. The study begins by conceptualizing A&BI capability as a third-order multidimensional construct that is manifested in three secondary sub-constructs namely: A&BI management capability, A&BI talent capability and A&BI technology capability. A&BI is relatively an emerging phenomenon with several uncertainties about its business value in organizations. A few conceptual works have posited enabling role of A&BI capability. However, it is still unclear as to what goes into developing this capability and its consequences on organizational performance. This study was therefore carried out to better understand this commonly observed but understudied A&BI fundamental building blocks and their intended consequence on performance. Thus, I refined the conceptualization and measurement of A&BI capability as a latent construct reflected in its three sub-dimensions.

Using a survey method conducted in 194 healthcare organizations, I empirically tested a research model that was developed based on the literature and case study. The results suggested that A&BI capability enables performance improvements in healthcare organizations. Furthermore, study findings also revealed that A&BI and organizational business alignment significantly influence healthcare organizations' performance as well as moderating the relationship between A&BI capability and performance improvement. Moreover, the results confirm my initial conceptualization that A&BI capability should be reflectively measured by three sub-constructs as supported by strong confirmatory factor analysis results.

Although some studies highlight the importance of management, talent and technology capability in other research context, this study draws on RBV theory and entanglement view of socio-materialism in proposing an integrated A&BI model and its overall impacts on healthcare organizations performance. A very important strength of this study however is that data was collected from multiple healthcare organizations to empirically test the research model. Overall, the findings from this study leads to a better understanding of A&BI building blocks as well as the relationship among A&BI-

organizational alignment-performance in healthcare organizations context. Hopefully, findings from the study open up further discussion and advances theory to generate a more holistic, comprehensive understanding about A&BI capability building and its consequences.

CHAPTER V

CONCLUSION OF OVERALL STUDY

This dissertation has investigated the impact of analytics and business intelligence (A&BI) techniques, capabilities and applications on healthcare organizations performance using a mixed method (qualitative and quantitative) research approach. Two major research studies were conducted to accomplish the main objective of this dissertation.

In Study 1, I examined how healthcare organizations value chain framework has significantly been impacted by the increasing adoption and use of information technology and related analytics and business intelligence systems. Due to the constant changes in the current healthcare ecosystem, care delivery services and value creation that goes along with it are also changing significantly. Using open-ended semi-structured interview in a large healthcare organization with five affiliate care providing organizations, it was discovered that the existing HCVC framework is currently outdated and hence, there was a need to revise and update the framework to meet the current healthcare organizations' care giving practices under the new ACO regulation.

Consequently, a revised framework is empirically provided using findings from interview responses gathered from 30 interviewees comprising of health IT employees, healthcare executives, physicians, nurses, and other clinicians. The revised HCVC framework is more reflective of how healthcare organizations are currently creating and delivering value to consumers by remotely engaging the general population using IT to ensure that consumers stay healthy so that they don't have to come to the hospital for care services. The revised framework also showcases which specific IT enabled analytics and business intelligence systems, techniques and applications are currently being applied within the various domains of the value HCVC framework.

Key finding from this study is that healthcare organizations are now investing more in IT-enabled A&BI in the support activity domain of their value chain framework than they are on the primary activity domain. The fundamental reason for the high investment in IT-enabled A&BI systems, techniques and process in the support activities of the new value chain activities of healthcare organizations can be attributed to the recent shifts in focus on care delivery that was introduce by ACO act. Thus, the new ACO act has propelled healthcare organizations to now be more proactive and agile in providing care and services that are geared towards reaching the healthy masses of the population with advanced technology-driven systems, techniques and process. As a result, healthcare organizations are currently investing more on information technology-driven analytics and business intelligence systems that is expected to facilitate remote monitoring of consumer behaviors and also help influence decisions of their consumers.

The resulting revised HCVC framework from Study 1 will contribute significantly to both literature and practice. In the case of academia, the revised framework opens a great deal of research opportunities to refine the framework or empirically test some potential relationships between elements within the framework. For healthcare practice, the revised framework will serve as a guide to other healthcare organizations that are currently in the process of transitioning from the old system or framework of value creation and delivery to the new system under the current ACA and ACO regulation.

In Study 2, I empirically developed and validated a theory of A&BI strategy that shows how healthcare organizations can build a strong A&BI capability and leverage this capability to improve their overall performance. The study begins by conceptualizing A&BI capability as a third-order multidimensional construct that is manifested in three secondary sub-constructs namely: A&BI management capability, A&BI talent capability and A&BI technology capability. A&BI is relatively an emerging phenomenon with several uncertainties about its business value in organizations. A few conceptual works have posited enabling role of A&BI capability. However, it is still unclear as to what goes into developing this capability and its consequences on organizational performance. This study was therefore carried out to better understand this commonly observed but understudied A&BI fundamental building blocks and their intended consequence on performance. Thus, I refined the conceptualization and measurement of A&BI capability as a latent construct reflected in its three sub-dimensions.

Using a survey method conducted in 194 healthcare organizations, I empirically tested a research model that was developed based on the literature and case study. The results suggested that A&BI capability enables performance improvements in healthcare organizations. Furthermore, study findings also revealed that A&BI and organizational business alignment significantly influence healthcare organizations' performance as well as moderating the relationship between A&BI capability and performance improvement. Moreover, the results confirm my initial conceptualization that A&BI capability should be reflectively measured by three sub-constructs as supported by strong confirmatory factor analysis results.

Although some studies highlight the importance of management, talent and technology capability in other research context, this study draws on RBV theory and entanglement view of socio-materialism in proposing an integrated A&BI model and its overall impacts on healthcare organizations performance. A very important strength of this study however is that data was collected from multiple healthcare organizations to empirically test the research model.

Overall, the findings from this study leads to a better understanding of A&BI building blocks as well as the relationship among A&BI-organizational alignment-performance in healthcare organizations context. Hopefully, findings from the study open up further discussion and advances theory to generate a more holistic, comprehensive understanding about A&BI capability building and its consequences.

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APPENDIX A

SURVEY INSTRUMENT AND QUESTIONNAIRE

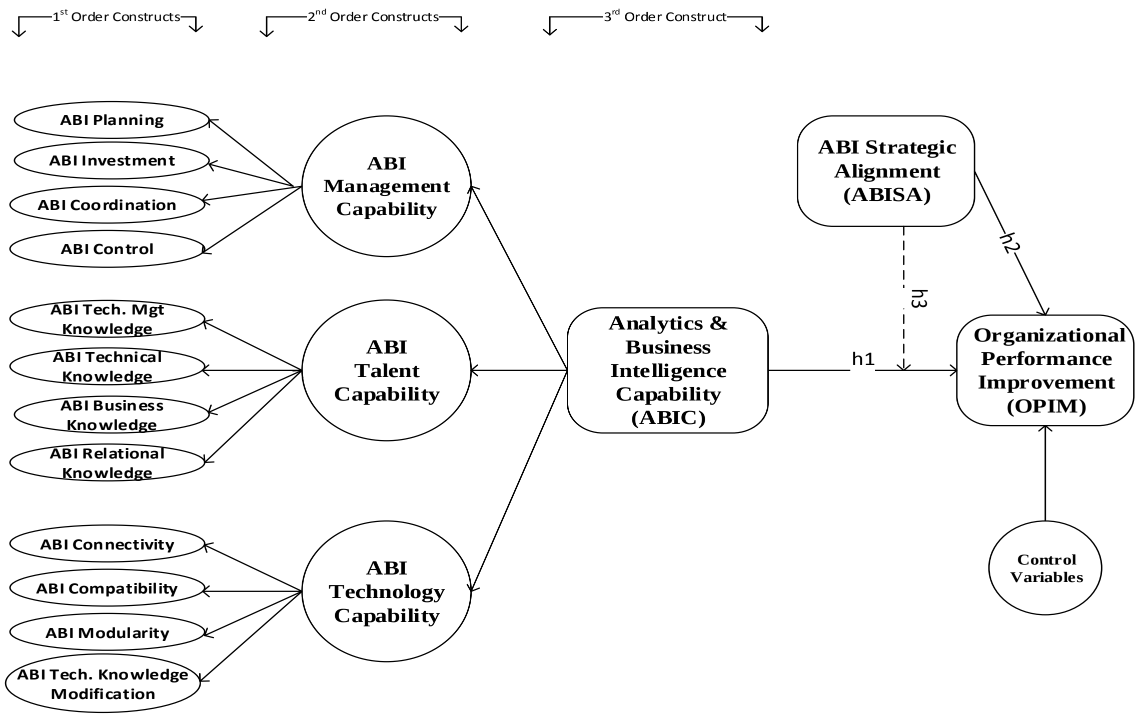

Figure 25. Research Model Used to Test Hypotheses

Table 43. Construct Definition, Survey Instrument and Sources

#	Construct	Definition	Sub-construct	Items	Source
1	Analytics & Business Intelligence (ABI) Organizational Management Capability (ABIOMC)	ABIOMC is an important aspect of ABIC ensuring that solid ABI related decisions are made by applying proper	**ABI Planning (ABIP)**	1) We continuously examine innovative opportunities for strategic use of ABI. 2) We enforce adequate plans for the introduction and utilization of ABI activities.	Boynton et al. (1994); Kim et al. (2012); Sabherwal, (1999); Segars and Grover, (1999)

		management framework.	ABI Investment Decision (ABID) ABI Coordination (ABICo)	3) We perform ABI planning process in systematic and formalized ways. 4) We frequently adjust ABI plans to better adapt to changing conditions and needs. 1) When we make ABI investment decision, we think about and estimate their consequences 2) When we make ABI investment decisions, we consider and project about how much these options will help end-users make quick decision. 3) When we make ABI investment decisions, we think about and estimate the cost of training that end-users will need. 4) When we make ABI investment decisions, we consider and estimate the time managers will need to spend overseeing the change. 1) Our ABI group and other	Kim et al. (2012); Ryan et al. (2002); Sabherwal (1999). Boynton et al. (1994); DeSanctis and Jackson, (1994); Karimi et al. (2001); Kim et al. (2012); Li et al. (2003)

			ABI Control (ABICtl)	employees in my organization meet frequently to discuss important issues 2) Our ABI group and other employees from various departments frequently attend cross-functional meetings in my organization. 3) Our ABI group and other line employees coordinate their efforts harmoniously in my organization. 4) In my organization, information is constantly shared between ABI and other line. 1) The responsibility for ABI development is clear in my organization. 2) We are confident that ABI project proposals are properly appraised in my organization. 3) We constantly monitor the performance of ABI functions in my organization. 4) Our ABI department is clear about	Karimi et al. (2001); Kim et al. (2012)

				performance criteria.	
2	Analytics & Business Intelligence (ABI) Talent Capability (ABITAC)	ABITLC represents the ability of ABI personnel within the organization to perform assigned tasks in a huge data environment. Thus, the ability of firm's ABI employees to apply their special knowledge and skills acquired through and experience to solve a business problem in such a way that is very rare and costly to imitate.	**ABI Technology Management Knowledge (ABITMK)**	1) Our ABI personnel show superior understanding of technological trends. 2) Our ABI personnel show superior ability to learn new technologies. 3) Our ABI personnel are very knowledgeable about critical factors for the success of our organization. 4) Our ABI personnel are very knowledgeable about the role of ABI as a means, not an end.	Kim et al. (2012); Byrd (2000); Tippins and Sohi (2003)
			ABI Technical Knowledge (ABITecK)	1) Our ABI personnel are very capable in terms of programming skills. 2) Our ABI personnel are very capable in terms of managing project life cycles. 3) Our ABI personnel are very capable in the areas of data and network management and maintenance. 4) Our ABI personnel create very capable decision support systems	Boar (1995); Broadbent et al. (1999); Kim et al. (2012); Lee et al. (1995); Byrd (2000)
			ABI Business Knowledge (ABIBK)		Duncan (1995); Kim et al. (2012); Byrd (2000); Tesch et al. (2003)

			ABI Relational Knowledge	driven by analytics. 1) Our ABI personnel understand our organization's policies and plans at a very high level. 2) Our ABI personnel are very capable in interpreting business problems and developing appropriate technical solutions. 3) Our ABI personnel are very knowledgeable about business functions. 4) Our ABI personnel are very knowledgeable about the business environment. 1) Our ABI personnel are very capable in terms planning, organizing, and leading projects. 2) Our ABI personnel are very capable in terms of planning and executing work in a collective environment. 3) Our ABI personnel are very capable in terms of teaching others. 4) Our ABI personnel work closely with	Boar (1995); Duncan (1995); Jiang et al. (2003); Kim et al. (2012); Lee et al. (1995); Byrd (2000)

				customers and maintain productive user/client relationship.	
3	Analytics & Business Intelligence (ABI) Technology Capability (ABITEC)	ABITEC is an aspect of ABIC which essentially refers to the flexibility in the use of ABI platforms in terms of their connectivity of cross-functional data, compatibility of multiple platforms and modularity in model building.	**ABI Connectivity (ABIC)** **ABI Compatibility (ABIComp)**	1) Compared to other organizations, my organization has foremost availability of ABI systems. 2) All remote, branch, and mobile offices are connected to the central office for ABI. 3) My organization utilizes open systems network mechanisms to boost ABI connectivity. 4) There are no identifiable communications bottlenecks within our organization when sharing ABI insights. 1) Software applications can be easily transported and used across multiple ABI	Duncan (1995); Kim et al. (2012); Byrd (2000) Duncan (1995); Kim et al. (2012); Byrd (2000)

			ABI Modularity (ABIMod)	platforms in my organization. 2) Our user interfaces provide transparent access to all platforms and applications. 3) ABI-driven information is shared seamlessly across our organization, regardless of location. 4) Our organization provides multiple ABI interfaces or entry points for external end-users.	Broadbent et al. (1999); Duncan (1995); Kim et al. (2012); Byrd (2000)
			ABI Technology Knowledge Upgrade (ABITKU)	1) Reusable software modules are widely used in new ABI model development in my organization. 2) End-users utilize object-oriented tools to create their own ABI applications in my organization. 3) Object-oriented technologies are utilized to minimize the development time for new ABI applications. 4) Applications can be adapted to meet a variety of needs during ABI	Akter et al. (2016); Broadbent et al. (1999); Duncan (1995); Kim et al. (2012); Byrd (2000)

				tasks in my organization. 1) Our ABI personnel are very knowledgeable about the current and emerging analytics tools and technologies. 2) Our ABI personnel are given the opportunity to grow their knowledge by taking short courses that enable them sharpen their savvy skills. 3) Our ABI personnel frequently attend conferences to learn from what others are doing and how. 4) My organization constantly provides training needs to ABI personnel to enhance their performance.	
4	Analytics & Business Intelligence Capability (ABIC)	ABIC is a second-order construct which comprise of a combination of ABIOMC, ABITAC, and ABITEC. It basically implies the ability of organizations to effectively	**Latent construct measured through:** • **ABIOMC** • **ABITLC** • **ABITEC**	NA	NA

		apply a combination of resources and knowledge in analytics and BI to solve business problems.			
5	Analytics & Business Intelligence (ABI) - Organizational Strategic Alignment (ABIOSA)	ABIOSA is also a second-order construct defined as the strategic alignment and integration of ABI and organizational mission and vision in order to enable organization meet or exceed its performance goals and targets. BIOSA, in other words, implies the characteristics of a strategic organizational capability that can help firms match resources with changing market opportunities.	**ABI-Organizational Strategic Alignment (ABI-OSA)**	1) My organization's ABI plan aligns with the overall mission, goals, objectives, and strategies. 2) My organization's ABI plan contains quantified goals and measurable objectives. 3) My organization's ABI plan contains detailed action plans/strategies that support company direction. 4) My organization's top level management welcomes inputs and ideas from ABI department when making strategic decision.	Akter et al. (2016); Setia and Patel (2013)
6	Organizational Performance Improvement (OPIM)	OPIM is defined as organizational performance improvement realized through ABI-	**Organizational performance**	Using ABI has significantly improved performance in the following areas in the past three years in my organization:	Akter et al. (2016); Tippins and Sohi (2003)

		driven capabilities and techniques	**improveme nt (OPIM)**	1) patient care giving 2) patient engagement via enhanced communication 3) Patient satisfaction 4) Reduced Emergency Department crowding 5) Profit margin 6) Return on investment	

The Survey Questions

This is a short survey designed to capture analytics and business intelligence (A&BI) capability information within organizations. We want to essentially investigate how healthcare organizations are building their A&BI capabilities which they, in turn, leverage to enhance their overall performance.

The survey will take approximately 20 minutes and we will share the aggregated findings with you - if you will provide your contact information at the end of the survey. Institutional Review Board (IRB) has determined that this study does not constitute human subjects research as defined under federal regulations [45 CFR 46.102 (d or f)] and does not require IRB approval.

We look forward to your inputs and participation to help shape the minds of our future business leaders! If you have any question regarding this study or survey, please contact either Dr. Lakshmi Iyer (Lsiyer@uncg.edu; 336-334-4984) or Mr. Rudolph Bedeley (rtbedele@uncg.edu; 336-536-2240). We thank you for your time and cooperation !

Q1 Please indicate the approximate number of Full Time Employees (FTE) in your organization:

- ❍ 0-19 (1)
- ❍ 20-99 (2)
- ❍ 100-249 (3)
- ❍ 250-499 (4)
- ❍ 500-999 (5)
- ❍ 1000-2499 (6)
- ❍ 2500-4999 (7)
- ❍ 5000+ (8)

Q2 Approximately how many years has your organization been in business?

- ❍ < 1 year (1)
- ❍ 1-5 years (2)
- ❍ 6-10 years (3)
- ❍ 11-15 years (4)
- ❍ 16-20 years (5)
- ❍ 20+ years (6)

Q3 Under which of the following industry sector does your organization fall?

- ❍ Private healthcare (1)
- ❍ Public healthcare (2)
- ❍ Other (please specify) (3) ____________________

Q4 How would you classify your organization's level of technology use based on the following categories?

- ❍ High tech (demonstrated healthcare outcomes based on the organization's implementation of current and emerging technology tools, systems and processes) (1)
- ❍ Moderate tech (implementing current and emerging technology tools, systems and processes but we are yet to realize outcomes) (2)
- ❍ Low tech (looking into implementing emerging technology tools, systems and processes) (3)

Q5 Please indicate your age group by selecting one of the following options?

- ❍ 18-25 years (1)
- ❍ 26-35 years (2)
- ❍ 36-45 years (3)
- ❍ 46-55 years (4)
- ❍ 56+ years (5)

Q6 Your gender is...?

- ❍ Male (1)
- ❍ Female (2)

Q7 What is your level of education?

- ❍ No formal education (1)
- ❍ High school diploma (2)
- ❍ Associate degree from community college (3)
- ❍ Four year college degree (BSc., BA, etc.) (4)
- ❍ Postgraduate degree (Masters/PhD) (5)

Q8 How many years of analytics, business intelligence and/or IT experience do you have?

- ❍ < 1 yer (1)
- ❍ 1-5 years (2)
- ❍ 6-10 years (3)
- ❍ 11-15 years (4)
- ❍ 16-20 years (5)
- ❍ 20+ years (6)

Q9 Which of the following best describes your job title or role in your current organization?

- ❍ Analyst (1)
- ❍ Business intelligence (BI) personnel (2)
- ❍ IS/IT Unit Manager (3)
- ❍ Business Development Manager (4)
- ❍ Human Resource Personnel/Manager (5)
- ❍ Other (please provide title such as Chief Analytics Officer, VP of Sales, Clinician, Marketing Manager, etc.) (6) ____________________

Q10 Under which of the following industry categories does your organization fall?

- ❍ Healthcare (1)
- ❍ Manufacturing (2)
- ❍ Retail (3)
- ❍ Banking and Finance (4)
- ❍ Communication (5)
- ❍ Travel/Transportation (6)
- ❍ Energy/Utilities (7)
- ❍ Government (e.g. Education, Law Enforcement, Military, etc.) (8)
- ❍ Other (please specify, e.g. consulting, service, etc.) (9) ____________________

Q11 Analytics and BI (ABI) Planning (ABIP): For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	agree (6)	Strongly agree (7)
We continuously examine innovative opportunities for strategic use of ABI? (1)	❍	❍	❍	❍	❍	❍	❍
We enforce adequate plans for the introduction and utilization of ABI activities? (2)	❍	❍	❍	❍	❍	❍	❍
We perform ABI planning process in systematic and formalized ways? (3)	❍	❍	❍	❍	❍	❍	❍
We frequently adjust ABI plans to better adapt to changing conditions and needs? (4)	❍	❍	❍	❍	❍	❍	❍

Q12 Analytics and BI (ABI) Investment Decision (ABIID):For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	agree (6)	Strongly agree (7)
When we make ABI investment decision, we think about and estimate their consequences? (1)	❍	❍	❍	❍	❍	❍	❍
When we make ABI investment decisions, we consider and project about how much these options will help end-users make quick decision? (2)	❍	❍	❍	❍	❍	❍	❍
When we make ABI investment decisions, we think about and estimate the cost of training that end-users will need? (3)	❍	❍	❍	❍	❍	❍	❍
When we make ABI investment decisions, we consider and estimate the time managers will need to spend overseeing the change? (4)	❍	❍	❍	❍	❍	❍	❍

Q13 Analytics and BI (ABI) Coordination (ABICo): For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree(4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Our ABI group and other employees in my organization meet frequently to discuss important issues? (1)	❍	❍	❍	❍	❍	❍	❍
Our ABI group and other employees from various departments frequently attend cross-functional meetings in my organization? (2)	❍	❍	❍	❍	❍	❍	❍
Our ABI group and other line employees coordinate their efforts harmoniously in my organization? (3)	❍	❍	❍	❍	❍	❍	❍
In my organization, information is constantly shared between ABI and other line employees? (4)	❍	❍	❍	❍	❍	❍	❍

Q14 Analytics and BI (ABI) Control (ABICtl): For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
The responsibility for ABI development is clear in my organization? (1)	❍	❍	❍	❍	❍	❍	❍
We are confident that ABI project proposals are properly appraised in my organization? (2)	❍	❍	❍	❍	❍	❍	❍
We constantly monitor the performance of ABI functions in my organization? (3)	❍	❍	❍	❍	❍	❍	❍
Our ABI department is clear about performance criteria? (4)	❍	❍	❍	❍	❍	❍	❍

Q15 Analytics and BI (ABI) Technology Management Knowledge (ABITMK):For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Our ABI personnel show superior understanding of technological trends? (1)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel show superior ability to learn new technologies? (2)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel are very knowledgeable about critical factors for the success of our organization? (3)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel are very knowledgeable about the role of ABI as a means, not an end? (4)	❍	❍	❍	❍	❍	❍	❍

Q16 Analytics and BI (ABI) Technical Knowledge (ABITecK):For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Our ABI personnel are very capable in terms of programming skills? (1)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel are very capable in terms of managing project life cycles? (2)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel are very capable in the areas of data and network management and maintenance? (3)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel create very capable decision support systems driven by analytics? (4)	❍	❍	❍	❍	❍	❍	❍

Q17 Analytics and BI (ABI) Business Knowledge (ABIBK):For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Our ABI personnel understand our organization's policies and plans at a very high level? (1)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel are very capable in interpreting business problems and developing appropriate technical solutions? (2)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel are very knowledgeable about business functions? (3)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel are very knowledgeable about the business environment? (4)	❍	❍	❍	❍	❍	❍	❍

Q18 Analytics and BI (ABI) Relational Knowledge (ABIRK):For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Our ABI personnel are very capable in terms planning, organizing, and leading projects? (1)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel are very capable in terms of planning and executing work in a collective environment? (2)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel are very capable in terms of teaching others? (3)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel work closely with customers and maintain productive user/client relationship? (4)	❍	❍	❍	❍	❍	❍	❍

Q19 Analytics and BI (ABI) Connectivity (ABIC):For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Compared to other organizations, my organization has foremost availability of ABI systems? (1)	❍	❍	❍	❍	❍	❍	❍
All remote, branch, and mobile offices are connected to the central office for ABI? (2)	❍	❍	❍	❍	❍	❍	❍
My organization utilizes open systems network mechanisms to boost ABI connectivity? (3)	❍	❍	❍	❍	❍	❍	❍
There are no identifiable communications bottlenecks within our organization when sharing ABI insights? (4)	❍	❍	❍	❍	❍	❍	❍

Q20 Analytics and BI (ABI) Compatibility (ABIComp):For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Software applications can be easily transported and used across multiple ABI platforms in my organization? (1)	❍	❍	❍	❍	❍	❍	❍
Our user interfaces provide transparent access to all platforms and applications? (2)	❍	❍	❍	❍	❍	❍	❍
ABI-driven information is shared seamlessly across our organization, regardless of location? (3)	❍	❍	❍	❍	❍	❍	❍
Our organization provides multiple ABI interfaces or entry points for external end-users? (4)	❍	❍	❍	❍	❍	❍	❍

Q21 Analytics and Business Intelligence (ABI) Modularity (ABIMod):For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Reusable software modules are widely used in new ABI model development in my organization? (1)	❍	❍	❍	❍	❍	❍	❍
End-users utilize object-oriented tools to create their own ABI applications in my organization? (2)	❍	❍	❍	❍	❍	❍	❍
Object-oriented technologies are utilized to minimize the development time for new ABI applications? (3)	❍	❍	❍	❍	❍	❍	❍
Applications can be adapted to meet a variety of needs during ABI tasks in my organization? (4)	❍	❍	❍	❍	❍	❍	❍

Q22 Analytics and business intelligence (ABI) Technology Knowledge Upgrade (ABITKU):For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Our ABI personnel are very knowledgeable about the current and emerging analytics tools and technologies? (1)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel are given the opportunity to grow their knowledge by taking short courses that enable them sharpen their savy skills? (2)	❍	❍	❍	❍	❍	❍	❍
Our ABI personnel frequently attend conferences to learn from what others are doing and how? (3)	❍	❍	❍	❍	❍	❍	❍
My organization constantly provides training needs to ABI personnel to enhance their performance? (4)	❍	❍	❍	❍	❍	❍	❍

Q23 Analytics and BI - Organizational Business Strategic Alignment (ABI-OBSA):For each of the following questions, please provide your answer by checking the appropriate option beside the question.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
My organization's ABI plan aligns with the overall mission, goals, objectives, and strategies? (1)	❍	❍	❍	❍	❍	❍	❍
My organization's ABI plan contains quantified goals and measurable objectives? (2)	❍	❍	❍	❍	❍	❍	❍
My organization's ABI plan contains detailed action plans/strategies that support company direction (3)	❍	❍	❍	❍	❍	❍	❍
My organization's top level management welcomes inputs and ideas from ABI department when making strategic decision? (4)	❍	❍	❍	❍	❍	❍	❍

Q24 Organizational Performance (OPER):Using ABI has significantly improved performance in the following areas in at least the past 3 years in my organization?

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Patient care giving? (1)	❍	❍	❍	❍	❍	❍	❍
Patient engagement via enhanced communication? (2)	❍	❍	❍	❍	❍	❍	❍
Patient satisfaction (3)	❍	❍	❍	❍	❍	❍	❍
Reduced Emergency Department crowding? (4)	❍	❍	❍	❍	❍	❍	❍
Return on investment? (5)	❍	❍	❍	❍	❍	❍	❍
Profit margin? (6)	❍	❍	❍	❍	❍	❍	❍

Please kindly provide your email address if you are interested in receiving a copy of the research report for this study.

Thank you so much for taking the time to complete this survey. This study is a part of Mr. Rudolph Bedeley's dissertation in fulfillment of his doctoral degree requirement at the University of North Carolina at Greensboro, NC, USA.

In case you have any questions or suggestions about this study, please do not hesitate to contact Mr. Bedeley (at rtbedele@uncg.edu) or his Dissertation Advisor (Dr. Lakshmi Iyer; lsiyer@uncg.edu).

Thank you!

APPENDIX B

CODES AND INTERVIEW PROTOCOL FOR QUALITATIVE RESEARCH

Table 44. Codes for Qualitative Data Analysis

• Analytics • Intelligence • Business intelligence (BI) • Analytics & Business intelligence (A&BI) • Capability • Analytics projects • Business intelligence projects • Top management • Top management leadership • Leadership • Top management commitment • Commitment • Top management support • IT business alignment • Strategy • Value • Project success • Project objectives • Support • Data • Big data • Data warehouse • Efficiencies • Business applications • Technology application • Analytics techniques • Data science • Business insight	• Satisfaction • Success • Communication • Open communication • IT project • Business project • Accountability • Team membership • Organizational goals • Organizational performance • Organizational performance improvement • IT involvement • Involvement • Training • Descriptive analytics • Predictive analytics • Prescriptive analytics • Proactive • Insight • Information • Decision support • Decision making • Business use case • Business analyst • Financial performance improvement • Discovery • Structured data • Unstructured data	• Interactions • Dedicated employees • Project culture • Collective goals • Challenges • Implementation • Success • Process improvement • Chief Information Officers (CIOs) • A&BI organizational management capability • A&BI planning • A&BI investment • A&BI coordination • A&BI control • A&BI talent capability • A&BI technology management knowledge • A&BI technical knowledge • A&BI business knowledge • A&BI relational knowledge • A&BI technology capability • A&BI connectivity • A&BI compatibility • A&BI modularity • A&BI capability

INTERVIEW PROTOCOL

Background

Interviews were conducted over 10month period between May 2016 – February 2017 by principal investigator Rudolph Bedeley. Dr. Lakshmi Iyer participated in some of the interviews as well. All interviewing was conducted in either a conference room of participating organization or in the private offices of interviewees of the same organization. Interviews were conducted behind closed doors in order to minimize distractions that might occur. Each interview lasted for an average of 45 minutes. The interview was conducted using open-ended interview protocol although an initial set of questions were shared with the interviewees.

The selected interviewees were from diverse background although majority of them came from two main groups within the organization: the business analytics (analyst) group, and business intelligence (BI) group.

Below is the detailed interview protocol with questions that were asked:

INTERVIEW PROTOCOL

Institution: **_The University of North Carolina at Greensboro____________________**

Principal Investigators (Name & Title):

1. Rudolph Bedeley
   Ph.D. Candidate, UNCG

2. Lakshmi S. Iyer (Ph.D.)
   Professor and Director of Graduate programs, UNCG

Interviewee: ____

Sections of Interview:

_______ A: Interviewee Background Information
_______ B: Understanding Current State of Analytics, Tools and Techniques used by
Healthcare Organizations
_______ C: Alignment of Analytics and Business Activities
_______ D: Benefits and Challenges from Analytics Use

A. Interviewee Background Information

1. How long have you been . . .

_______ at this organization?

_______ in your present position?

2. What is your highest level of education?
____
3. What is your role?
____
4. Organizational reach/size

___Regional ___State ___National ___Multi-National

B. Phase II: Understanding Current State of Analytics, Tools & Techniques

5. What does the term "*Business Anlytics*" mean to you from healthcare context?
____
____
____
____

6. Does the healthcare value chain framework presented in Figure 3 above makes sense to you?
____
7. How does your organization currently carry out its Analytics activities?
____
____
8. Can you please provide some perspective about the type of data you collect/store/analyze?

Structured:
____

Unstructured:
____

Semi structure:
____

Probe: do you collect other data such as voice, images, videos, etc.?

____

9. What type of analytics tools/techniques does your organization use in performing the following activities?

Admissions: ______; Care: _____; Discharge: _____; Marketing/Sales: _____; Service: ____;

Hospital Administration:

____

Information Services:

____

Diagnostics & Therapeutic Services:

____

10. Does your organization currently perform any of these types of analytics activities?

Descriptive:

____

Predictive:

____

Prescriptive:

____

11. Does your organization perform real-time analytics or ad-hoc-based analytics?

____

____

C. **Phase I: Alignment of Analytics & Business Activities**

12. At what level in your organization does Analytics "thought leadership" reside?

____

13. How does your company's Analytics strategic planning aligns with your current

i. IT activities:

____

ii. Business activities:

____

14. Why does your organization incorporate Analytics in its strategic initiative?

    ____

    ____

15. What is your vision or motivation for implementing Business Analytics as a strategic initiative within your organization?

    ____

    ____

16. Why would your organization hire a Chief Analytics Officer?

    ____

    ____

17. If you could ask me questions on why organizations use Analytics, what would they be?

    ____

    ____

D. Benefits and Challenges from Analytics Use

18. Do you see your organization deriving business value from Analytics use as it applies to the following?

    improving quality of care:

____

    improving financial performance:

____

19. Can you please highlight any challenges your organization is currently facing or will face in the future as a result of the adoption of emerging Analytics techniques or technology?

    ____

    ____

Post Interview Suggestions/Comments/Remarks:

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