Physician Practice Survival:

The Role of Analytics in Shaping the Future

by

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ABSTRACT

This dissertation joins an ongoing discussion in the business management and information technology literature surrounding the measurement of an organization's business analytic capability, the benefits derived from maturing the capability and the improvements being made toward maturity. The dissertation specifically focuses on the healthcare industry in the United States and more specifically independent physician practices specializing in orthopaedics. After an extensive literature review along with expertise from industry leaders and experienced academic faculty, a survey instrument was developed to measure organizational capabilities, technology capabilities and people capabilities which together measured an organizations overall business analytic capability maturity. The survey instrument was delivered to 89 C-suite executives in the target population. A response rate of 36% was achieved resulting in a total of 32 completed responses.

The research study provides evidence that improving an organization's business analytic capability leads to an improvement in the use of analytics to drive business performance. The research study also explored whether or not the use of analytics would improve business outcomes. The results were inconclusive. This could be due to the lag time between the use of analytics and business performance. In addition, the study did not have access to actual outcome data but rather asked the CEO's whether or not performance in several areas had improved, remained stable or had declined. This measure may not have been precise enough to provide the predictive value needed. As

such, this is an area that should be explored further. Finally, the research shows that over the past two years, physician practices have been focused on and successful in improving their business analytic capabilities. Despite these improvements, opportunities exist for physician practices to further their maturity, particularly in the areas of technology capabilities and people capabilities.

CHAPTER ONE:

INTRODUCTION

The challenges of managing healthcare costs and achieving clinical integration in today's payment environment is a national concern (Ashrafi et. al., 2014). Every participant in the healthcare systems needs to be focused on accelerating this journey in order to survive (Porter & Kaplan, 2014). The healthcare industry has begun to realize the importance of business intelligence as a tool to improve decision making and to generate actionable knowledge about opportunities for improvement (Ashrafi et al., 2014). In addition to having the data and business intelligence, an organization needs to have the capabilities to utilize this data in meaningful ways to improve its competitive advantage. According to their research, Davenport and Harris found a positive relationship between the use of analytics and business performance. (Davenport & Harris, 2007).

There is no doubt that healthcare organizations need to continue to drive a shift toward greater quality and lower cost. Throughout the research literature, the evidence is clear that healthcare organizations are building their capabilities to reach this goal. Most of the discussions in the literature focus on large healthcare systems throughout the United States, however independent physician practices continue to be prevalent and overcoming the challenges of adopting technologies and building analytic capabilities will be critical to these practice's success, particularly if they desire to stay independent. As a researcher and an executive of a physician practice specializing in orthopaedics, I have a professional interest in exploring ways to improve our physician practice's performance, its competitive edge and its long-term ability to maintain its independence. I am certainly not alone, other leaders in our industry share the same concerns and have formed trade organizations to share best practices. My professional interest has influenced the motivations for my research.

There are three motivations for this research study. The first motivation is that a business analytics capability has been shown to improve business performance and create competitive advantage (Davenport & Harris, 2007 and Cosic et al., 2012). The proliferation of electronic health record adoption has provided physician practices with more data than ever before. Incentives from payers to improve quality and reduce costs are rapidly increasing, In order to remain competitive, independent physician practices must be able to utilize the data they are capturing to improve patient care and reduce costs. The second motivation is that there has been limited research on the characteristics that drive the maturity of business analytics capabilities in the healthcare sector and none were found that specifically focused on physician practices. The third motivation is that developing an industry specific business capability maturity model and studying the organizational characteristics that drive maturity will inform physician practices on ways to improve their capabilities which could lead to improved business performance.

Background

According to Davenport and Harris in their book, *Competing on Analytics, the New Science of Winning*; analytics is defined as "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" (Davenport & Harris, 2007). According to the research highlighted in their book, the authors found a positive relationship between the use of analytics and business performance. Comparing high performers (those who outperformed their industry in terms of profit, shareholder return and growth) with low performers, they found that the majority of high performers strategically applied analytics in their daily performance (Davenport & Harris, 2007).

Since the Institute of Medicine issued its report, *"Crossing the Quality Chasm"* in 2001, citing the healthcare delivery system in America as fragmented, failing to provide consistency in quality of care and failing to make the best use of its resources; the healthcare industry has been under immense pressure to reduce cost and increase the quality of care provided. In addition, the Health Information Technology for Economic and Clinical Health (HITECH) Act, enacted in 2009, promoted the adoption and meaningful use of health information technology (Gold & McLaughlin, 2016). The pressure to improve quality and reduce cost coupled with the drive toward adoption of electronic health records has created an opportunity and a need for healthcare organizations to develop their analytic capabilities.

In his book, *Big Data at Work*, Davenport describes healthcare organizations as data disadvantaged because although electronic medical records are becoming more widespread, approximately 50% of the data housed in medical records consists of unstructured text. In addition, he notes that the challenge for the healthcare industry will be in how to make use of all the data (Davenport, 2014). Physician practices have been more reluctant to adopt electronic medical records primarily because the initial versions of electronic health records, while designed well to coordinate care between offices, were not well designed to assist physicians with the job to be done in the office

(Christensen et al., 2009). As such, it has been easier for doctors to continue to use paper or a data repository solution than to adopt an expensive electronic health record. Second, payment systems have not been aligned to encourage the adoption of an electronic health record (Christensen, et al., 2009).

While physician practices have been slower to adopt for the reasons noted above, their role in the care process and therefore, reducing the costs and improving quality is critical. Studies have suggested that physicians direct as much as 90% of total health spending (Kirchhoff, 2013). In today's environment, more incentives exist in the market through new payment models created by both the government (through Medicare) and commercial insurers. In addition, the government has begun to assess penalties to physician practices who fall below their peer groups in terms of quality and cost data. As such, independent physician practices have begun to change dramatically. Historically, physician practices in the U.S. were made up of small or solo practices. However, in the past several years, doctors have started merging their offices into larger practices or combining their practices with hospitals, insurance companies or physician management firms (Kirchhoff, 2013). Many physician practices desire to stay independent and have been working to develop strategies to retain their strength in the market while adopting the necessary but costly regulations. The effective use of analytics could provide a competitive advantage for a physician practice or become a necessary tool to survive. Either way, the role of analytics in healthcare will shape the future of healthcare delivery.

While there is progress in recognizing what is needed to drive success, the ability to successfully achieve what is needed is a journey unto itself. Organizations need a systematic method for developing their skills in any area; but especially in an area as complex as building an analytic capability. Maturity models are often used both in research and in practice, as a measure to evaluate the capabilities of an organization (De Bruin & Rosemann, 2005). A commonly cited maturity model is the Capability Maturity Model (CMM) developed by the Software Engineering Institute of Carnegie Mellon University. CMM was developed as a process-maturity framework designed to assist in the process of improving software development (Paulk et.al., 1993). CMM developed the concept that increased maturity results in an increase in the capability of the organization (Paulk et al. 1993). Maturity models generally consist of a maturity framework along with an assessment tool used to assess an organizations maturity along the framework. In their research de Bruin et al. noted more than 150 maturity models had been developed to measure maturity of, for example, IT Service Capability, Strategic Alignment, Innovation Management, Program Management, Enterprise Architecture and Knowledge Management (de Bruin et al. 2005) and since their publication others have emerged including Business Intelligence (Lahrmann et al. 2011) and Business Analytics (Davenport & Harris, 2007). The research proposed will utilize a maturity model as the systematic method for evaluating the business analytics capability of a physician practice specializing in orthopaedics.

Purpose

As noted above, research has shown that high performing organizations strategically applied business analytics in their daily operations (Davenport & Harris, 2007). Maturity models are commonly used in industry and in research as a systematic method of evaluating organizational capabilities. In addition, many of the models in existence have associated assessment tools in the form of surveys that seek to measure where an organization is along the maturity framework. Consistent with the motivations for this research, the study explores the following research questions:

1. How do we measure business analytic capability maturity in the healthcare sector and more specifically in physician practices?
2. What are the benefits in terms of outcomes for physician practices that are more mature in their business analytic capability?
3. How are physician practices improving their business analytic capabilities?

Based on a review of the research literature on business analytics capability models, it is anticipated that the more mature a practice is in their business analytic capabilities the more likely they will use analytics for driving business decisions. It is further anticipated that the increased use of analytics to drive business performance will improve outcomes in terms of financial results, patient satisfaction, market share and quality of care.

Significance

As mentioned earlier in this chapter, the challenges of managing healthcare costs and achieving clinical integration in today's payment environment is a national concern (Ashrafi et. al., 2014). In order for independent physician practices to survive, they will need to overcome the challenges of adopting technologies and build analytic capabilities to measure cost, build scale and improve quality. The population surveyed in this research study are all independent physician practices. The orthopaedics specialty was chosen for convenience as I am a chief financial officer for a large orthopaedic practice in the United States.

Limitations

Data was not available with regards to actual physician practice outcomes. Instead, survey questions were constructed in an attempt to measure whether or not the organization's outcomes were improving, stable or declining. In addition, some practices may not currently measure all of the outcomes this study sought to explore. This resulted in some missing data.

The population surveyed was a small subset of the healthcare industry: physician practices specializing in orthopaedics. As such, the results of the analysis may not be generalizable to other healthcare organizations and particularly to other organizations outside of healthcare.

Summary

In order to explore the research questions of interest, the first step was to conduct a comprehensive review of the research literature on this topic. The next chapter describes the process and walks through the outcomes of the literature review.

CHAPTER TWO:

LITERATURE REVIEW

In the first phase of the research, an extensive literature review was conducted of both maturity models in general and then of business analytics and business intelligence maturity models. The purpose of the extensive literature review was to explore how a business analytic capability has been measured in the literature. This will then inform the development of a research model to explore the benefits to practices that are more mature in their capabilities. In addition, it will enable the creation of a survey instrument to be used to measure business analytic maturity of physician practices specializing in orthopaedics.

Maturity describes a state of being complete or ready (Lahrmann et al., 2011). Maturity models are often used both in research and in practice, as a measure to evaluate the capabilities of an organization (De Bruin & Rosemann, 2005). A commonly cited maturity model is the Capability Maturity Model (CMM) developed by the Software Engineering Institute of Carnegie Mellon University. CMM was developed as a process-maturity framework designed to assist in the process of improving software development (Paulk et.al., 1993). CMM developed the concept that increased maturity results in an increase in the capability of the organization (Paulk et al. 1993).

The properties of a maturity model generally include: a framework, the dimensions being measured, levels of maturity, the stages of maturity, and the assessment approach (Lahrmann et al., 2011; De Bruin & Freeze, 2005).

Maturity frameworks can be descriptive, prescriptive or comparative in nature (De Bruin & Freeze, 2005). This research study will use a prescriptive framework as the model provides context around the scoring to enable an organization to assess areas of opportunity to improve its capabilities. In addition, the model will compare the maturity levels today with the maturity levels for the same practices two years ago. This will provide additional context for the physician practices in the industry to determine how physician practices' are maturing in their capabilities.

Another property of maturity models are their dimensions. Dimensions are the specific capabilities required with measures at each level of maturity defined (Lahrmann et al., 2011). The dimensions used in our study were developed from our literature review and from industry experience. The development of these dimensions along with the definition of each are discussed later in this chapter.

Most maturity models adopt variations on the Capability Maturity Model which uses five levels of maturity where the lowest level of maturity is represented as level one and the highest level of maturity is represented as level five (De Bruin & Freeze, 2005). Different names have been used to describe each level but the hierarchy is common in the research literature. Table 1 highlights the variation in both number of levels and naming conventions used in the literature. The levels used in this study are discussed in further detail following Table 1.

Table 1. Levels and Stages of Maturity

Article Reference	Levels of Maturity	Stages of Maturity
Cosic et. al., 2012	Non-Existent: the organization does not have this capability. Initial: the capability exists but is poorly developed Intermediate: the capability is well developed but there is much room for improvement Advanced: the capability is very well developed but there is still a little room for improvement Optimized: the capability is so highly developed that it is difficult to envision how it could be further enhanced.	Maturity score for each dimension and an overall maturity score
Davenport and Harris, 2007	Analytically Impaired: Desire to become more analytical but lack the will and skill to do so. Localized Analytics: Typical localized analytics approach to business intelligence with pockets of analytical activity Analytical Aspirations: grasp the value and promise of analytical competition, but face major capability hurdles and are a long way from overcoming them. Analytical Companies: on the verge of Analytical competition but face a few minor hurdles Analytical Competitors: Full maturity	Not specified
Tan et. al., 2011	Adopted from CMM: Initial, Defined, Repeated, Managed, Optimized.	4 Dimensions with 5 sub-dimensions
Lahrmann et. al., 2011	Deployment, Use, Impact	Not specified
De Bruin & Rosemann, 2005	Adopted from CMM, now referred to as CMMI: Initial, Defined, Repeated, Managed, Optimized.	maturity levels are defined at each dimension level
Raber et. al., 2012	Initiate, Harmonize, Integrate, Optimize, Perpetuate	maturity levels are defined at each dimension level
LaValle et al., 2010	Aspirational: The farthest from achieving their goals; often they are focusing on efficiency or automation of existing processes and searching for new ways to cut costs. Experienced: Looking beyond cost management; developing better ways to effectively collect, incorporate and act on analytics. Transformed: Substantial experience using analytics across a broad range of functions. Use analytics as a competitive differentiator and are already adept at organizing people, processes and tools to optimize and differentiate.	maturity levels are defined at each dimension level
Chuah, 2010	Initial, Managed, Defined, Qualitative Managed, Optimizing	maturity levels are defined at each dimension level
Russell, et. al., 2010	Conception – Ad hoc & Informal Analysis & Reporting Coalescence – Centralization and warehousing Saturation – Analytical Service Provisioning Diversification – Pervasive Integration and Ubiquity	Progression occurs through evolutionary chasms

Another aspect of maturity models is the method used to judge the levels of maturity. Levels can be measured using a continuous or a staged approach. Staged models require all the elements be met before moving to the next stage while continuous models allow for weighted averages or individual levels in different dimensions (Lahrmann et al., 2011). Table 1 highlights the different stages of maturity used in the literature. The approach used in this research study is a continuous model as weighted average scores are used to compare maturity levels.

Finally, maturity models are generally accompanied by an assessment approach. A quantitative approach using an electronic survey is recommended as it enables the collection of results that can provide consistent statistical analysis and improves comparability of results (DeBruin et al., 2005). Our research utilized a questionnaire that was developed from the dimensions defined from the literature review and discussed later in this chapter.

Maturity Model

Table 1 highlights both some commonalities and differences in the levels used by researchers to measure maturity. The most common number of levels is five which is consistent with the most commonly cited maturity model, CMM. This study will also use five levels and have adopted naming conventions and definitions based on the works of Davenport, Cosic and LaValle. Our five levels for the overall capability maturity score are defined as follows:

Non-Existent	The organization does not have this capability and does not use business analytics.
Initial	The organization may be using some localized analytics but has not begun to develop capabilities.

Aspirational	Understand the importance of building business analytics capability but are in the early stages.
Experienced	The organization has established capabilities.
Optimized	Capabilities are fully developed and high functioning.

The five maturity levels are depicted in the figure below. (See Figure 1.)

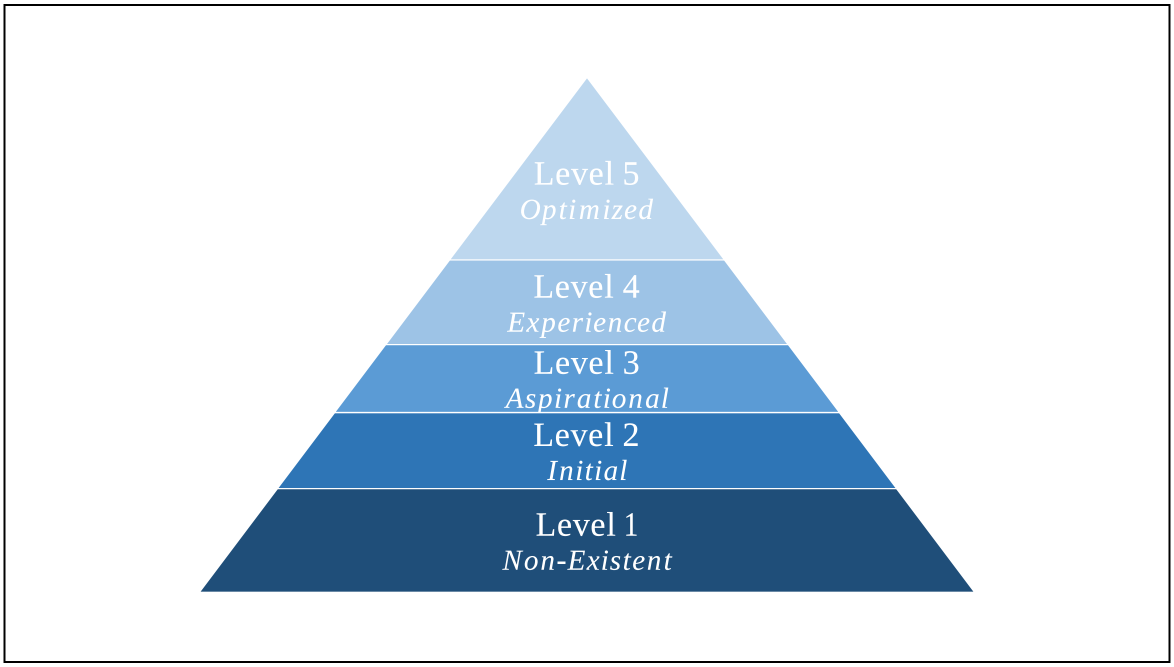


Figure 1. Maturity levels*
**Adapted from Davenport & Harris, 2007; Cosic et. al., 2012 and LaValle et. al., 2010.*

Dimensions of Maturity

As noted previously, an extensive literature review was conducted to assess the appropriate organizational characteristics and behaviors that would drive the organization's level of maturity in business analytics. The details of both the search terms used as well as the search results are provided in Appendix A. The search terms sought articles in both business analytics and business intelligence. Then, as each article was reviewed, any organizational characteristics or behaviors were noted. From these characteristics, several overall themes or dimensions emerged as noted below in Table 2.

Table 2. Dimensions of a Business Analytic Capability.

Dimension	**Description**	**References**
Strategy	The extent to which business analytic initiatives are linked with strategic objectives.	Davenport & Harris, 2007; Cosic et al., 2012; Cosic et. al., 2015; Lahrmann et. al., 2011; Brooks et al., 2015; De Bruin et al., 2005; Raber et al., 2012; LaValle et al., 2010; Holsapple et al., 2014; Shanks & Bekmamedova, 2012; Sharma et al., 2014; Isik et al., 2013;
Top Management Support	The extent to which the leadership sponsors and supports business analytic initiatives.	Davenport & Harris, 2007; Cosic et al., 2012; Cosic et al., 2015; Lahrmann et al., 2011; Brooks et al., 2015; Holsapple et al., 2014; Shanks & Bekmamedova, 2012; Seddon et al., 2016
Data Management	The extent to which a mechanism is in place for ensuring data used in business analytic initiatives is a fit for the purpose and meets the information requirements of the organization.	Davenport & Harris, 2007; Cosic et al., 2012; Cosic et al., 2015; Lahrmann et al., 2011; Brooks et. al., 2015; Tan et al., 2011; Raber et al., 2012; Ghosh & Scott, 2011; Ward et al., 2014; Shanks & Bekmamedova, 2012; Chuah 2010;
Data Quality	The extent of the organizations efforts in ensuring information quality.	Davenport & Harris, 2007; Lahrmann et al., 2011; Foshay & Kuziemsky, 2013; Brooks et al., 2015; Tan et al., 2011; Raber et al., 2012; Ward et al., 2014; Shanks & Bekmamedova, 2012; Isik et al., 2013; Chuah 2010; Seddon et al., 2016
Data Integration	The extent to which data is effectively integrated.	Davenport & Harris, 2007; Cosic et al., 2012; Cosic et al., 2015; Lahrmann et al., 2011; Brooks et al., 2015; Raber et al., 2012; Ghosh & Scott, 2011; Isik et al., 2013
People Skills	The extent to which individuals in the organization have analytic skills as well as the extent of those skills.	Davenport & Harris, 2007; Davenport et al., 2001; Cosic et al., 2012; Cosic et al., 2015; Lahrmann et al., 2011; Foshay & Kuziemsky, 2013; Brooks et al., 2015; LaValle et al., 2010; Ward et al., 2014; Seddon et al., 2016

Table 2. Dimensions of a Business Analytic Capability (Continued).

Dimension	Description	References
Training	The extent to which opportunities exist within the organization to develop analytic talent.	Cosic et. al., 2015; Davenport & Harris, 2007; Brooks et. al., 2015; De Bruin et al., 2005; Shanks & Bekmamedova, 2012; Seddon et al., 2016
Change Management	The extent to which management is effective in garnering acceptance for the use of analytics to drive decision making and implementing change as a result.	Davenport & Harris, 2007; Cosic et al., 2012; Cosic et al., 2015; Brooks et al., 2015; De Bruin et al., 2005; Seddon et al., 2016

The dimensions identified in Table 2 generally fell into one of three major business analytic capabilities: organizational capabilities (strategy and top management support; technology capabilities (data management, data quality and data integration) and people capabilities (skills, training and change management).

Other Impacts to Business Performance

The literature review also revealed several other impacts to business performance; one of which, was the usability of data in the organization. As noted by Ward et al., 2014; research has shown that users feel more confident in the decisions made when the data is provided in an easy to understand format. In addition to being visualized in a way that is easy to understand; users need to access the data timely, including real-time data in operational areas (Isik et al., 2013). In addition, research has shown that information access quality has a positive relationship on the use of business analytics (Popovic et al., 2012; Cosic et al., 2012 and 2015). For purposes of our research, usability is defined as the extent to which analytics are visualized and reported in a manner that is accessible and easy to use for decision making.

Use of Analytics

In various places throughout the literature, we noted articles that specifically link an organization's business analytic capability (BAC) maturity with the use of analytics. These articles indicate that it is the use of analytics that drives improved business performance. A summary of the articles linking BAC maturity with use of analytics to drive outcomes are listed in Table 3 below.

Table 3. Business Analytic Capability Drives the Use of Business Analytics.

Source	**Discussion of use and BAC**
Lahrmann et al., 2011	"…we conceptualize BI (business intelligence) maturity based on three interrelated concepts 'deployment', 'use' and 'impact'."
Shanks et al., 2012	"Having BA (business analytics) technology and BA capabilities alone is insufficient; insights gained from BA must be used to initiate value creating actions…"
Sharma et al., 2014	"…there is a need to gain a better understanding of how existing organizational structures, routines and decision making processes affect the ability of analysts and managers to generate insights from the use of business analytics."
Popovic et al., 2012	"While value … is the final success variable, use of the system is fundamental for certain benefits to occur."
Seddan et al., 2016	"Use analytic resources means usage of BI (business intelligence) technology by people across the organization. This BA (business analytic) usage is the fundamental driver of business value from BA. The reason is simple: no use, no benefits."

In addition, other articles include levels of use (depth and breadth) in describing organizations that are mature in their ability to derive value from analytics (Davenport & Harris, 2007). The depth of use for purposes of this study is defined as the depth of the insights sought from performance drivers through the use of the data (Davenport & Harris, 2007). The breadth of use for purpose of this study is defined as the use of analytics for data-driven decisions across a broad spectrum of performance drivers.

Research Constructs

The dimensions discussed above; organizational capabilities, technology capabilities and people capabilities represent the constructs that will be used to measure the organization's business analytic capability maturity. Other constructs that will be measured in the survey include usability, depth of use of analytics and breadth of use of analytics. Initial versions of the constructs and definitions identified above were provided to four healthcare industry executives and four academic advisors for their review and feedback. Their feedback was incorporated in the results presented above. The next step was to develop a survey instrument that would be used to measure each of these dimensions as well as the overall maturity of a healthcare organization.

Summary

The literature review conducted identified several key observations. First, it identified some common constructs used to measure a business analytic capability, which were; organizational capabilities, people capabilities and technology capabilities. Second, the usability of the data analytics was found to provide end users more confidence in their decision making and therefore, more likely to use analytics in their decision making. Next, a business analytic capability was found to lead to greater depth and breadth of use of analytics by the organization. Finally, the use of analytics to drive decision making was found to improve the business performance of the organization. In the next chapter, the development of a conceptual research model and a survey instrument are outlined and discussed.

CHAPTER THREE:

RESEARCH MODEL AND SURVEY INSTRUMENT

Building on the dimensions of maturity and other constructs identified in the literature review, a conceptual model was formed that encompasses all of the constructs and their relationships. Improving an organization's business analytic capability maturity will drive the use of analytics for decision making. It is the depth and breadth of use of analytics within an organization that will lead to improved business performance (see Figure 2 below).

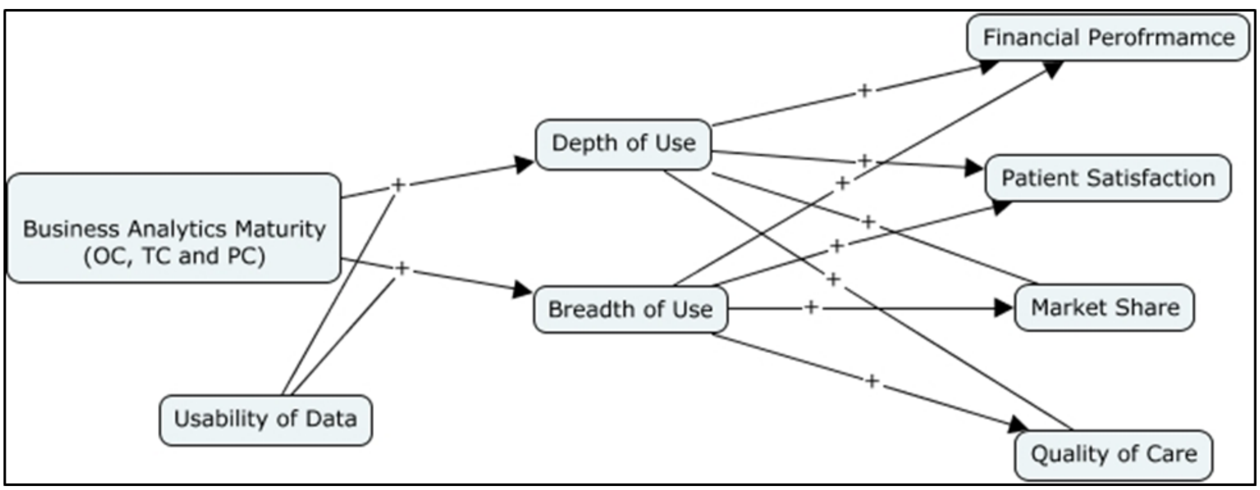


Figure 2. Business analytic capability conceptual model

As outlined in the conceptual model and based on the extensive literature review, we propose that building a business analytics maturity will improve both the depth of use of analytics and the breadth of use of analytics. We propose that the usability of analytics along with having a business analytics maturity will have a positive impact on an organization's depth and breadth of use of analytics. To that end, the following hypotheses are proposed:

H1a: Business analytics capability maturity is positively correlated with depth of use of analytics.
H1b: Business analytics capability maturity is positively correlated with breadth of use of analytics.
H1c: Usability of analytics together with business analytics capability maturity has a positive impact on the depth of use.
H1d: Usability of analytics together with business analytics capability maturity has a positive impact on the breadth of use.

Next, we propose that the depth of use of analytics and the breadth of use of analytics will be positively correlated to five different business outcomes. As noted in chapter one, our research questions specifically identified four key areas of performance that physician practices seek to continuously improve in order to remain viable: financial performance, patient satisfaction, market share, and quality of care. In order to assess financial performance; two key metrics were identified: patient revenues, which is an indicator of the practices ability to improve their revenue sources and compensation per physician which is a proxy for net income. The practices surveyed are physician owned and therefore; distribute the majority of their income to the physicians in the form of compensation. The second series of hypotheses proposes that the depth of use analytics and the breadth of use of analytics are positively correlated to financial performance. The hypotheses proposed are as follows:

H2a: Depth of use of analytics is positively correlated with improved financial performance as measured by patient revenues.
H2b: Breadth of use of analytics is positively correlated with improved financial performance as measured by patient revenues.
H2c: Depth of use of analytics is positively correlated with improved financial performance as measured by average physician compensation.

H2d: Breadth of use of analytics is positively correlated with improved financial performance as measured by average physician compensation.

The third series of hypotheses proposes that the depth and breadth of use analytics are positively correlated to patient satisfaction. The hypotheses proposed are as follows:

H3a: Depth of use of analytics is positively correlated with improved patient satisfaction.

H3b: Breadth of use of analytics is positively correlated with improved patient satisfaction.

The fourth series of hypotheses proposes that the depth and breadth of use analytics are positively correlated to market share. The hypotheses proposed are as follows:

H4a: Depth of use of analytics is positively correlated with improved market share.

H4b: Breadth of use of analytics is positively correlated with improved market share.

The fifth series of hypotheses proposes that the depth and breadth of use analytics are positively correlated to quality of care. The hypotheses proposed are as follows:

H5a: Depth of use of analytics is positively correlated with improved quality of care.

H5b: Breadth of use of analytics is positively correlated with improved quality of care.

Survey Instrument

In order to test these hypotheses, a questionnaire or survey instrument was created consisting of a series of questions intended to capture responses in order to measure each of the constructs identified in the hypotheses. The survey questions were developed using an extensive literature review as well as from industry experience. The questionnaire is provided in its entirety in Appendix B.

Business Performance Questions

As mentioned in chapter one, the healthcare industry has begun to realize the importance of business intelligence as a tool to improve decision making and to generate actionable knowledge about opportunities for improvement (Ashrafi et. al., 2014). Additionally, the areas of improvement needed in the healthcare industry are around quality improvement and reducing costs. As such, the business performance questions asked of the organization's surveyed included key measurements of these areas of the business. Also, as mentioned in chapter one, data was not available from all 92 practices in order to use actual business performance metrics. As such, five survey questions were asked to determine business performance in the following areas: financial performance, patient satisfaction, market share, and quality.

For financial performance, two common metrics are used by physician practices: total patient revenues and average compensation per physician. Patient revenues provides one picture of the overall health of the physician practice. Physician practices that are able to grow their top line revenues have a better chance of long-term survival. In addition to growing the top-line, physician practices need to reduce costs and manage operations efficiently. The physician practices surveyed were all privately-held, physician owned organizations. These organizations tend to payout any excess earnings to the physician owners. As a result, net income would not be an appropriate measure of overall financial performance. Instead, we used average physician compensation as a proxy for overall financial performance.

Patient satisfaction was also determined to be a critical outcome measure. The Centers for Medicare and Medicaid Services (CMS) now requires all physician practices over a certain size to measure patient satisfaction. These measures are used to compare practices performance against other practices and can result in a bonus payment or penalty takeback. In addition, as payers (insurance companies, government programs, and employers) shift more of the cost burden to patients, patient satisfaction becomes more critical than ever before to the long-term success of the practice.

As it relates to market share, in order for physician practices to stay competitive in their market they will need to build or at a minimum sustain their market share. The greater the market share, the greater the negotiating power with payers and with other healthcare providers along the continuum of care.

Finally, the healthcare industry has begun to pivot toward pay-for-performance payment models, away from the traditional fee-for-service models. As such, measuring and improving quality performance will be critical to the future success of a physician practice.

Maturity Capability Questions

In order to measure business analytic capability maturity, a series of questions were asked about each of the dimensions as noted in chapter two. These were listed in Table 2 of that chapter. The development of the questions were either taken directly from the literature review, modified from questions or statements in the literature review, or were new questions developed based on industry knowledge. This section outlines how each of the maturity capability questions were developed.

Organizational capability. Organizational capabilities include strategy and top management support. Strategy was defined in chapter 2 as the extent to which business analytic initiatives are linked with strategic initiatives. Top management support was defined in chapter 2 as the extent to which leadership sponsors and supports business analytic initiatives. The questions asked, the source and any modifications are outlined in table 4 below:

Table 4. Organizational Capability Questions.

Dimension	Question	Source/Form	Modifications
Strategy	Building and/or improving the ability to make data-driven decisions is a key part of our practice's strategy.	LaValle et. al., 2010/question	Added "Building and/or". Changed "top priority in our organization" to "key part of our practice's strategy."
Strategy	Our practice's strategic initiatives are linked to measurable outcomes.	Cosic et. al., 2015 and Sharma et. al., 2014	Several articles cited governance and the process of measuring results against expectations.
Strategy	Our practice predicts and prepares for the future by proactively evaluating scenarios and potential trade-offs.	LaValle et. al., 2010/question	"Our organization was changed to "Our Practice".
Top Management Support	Members of senior management are passionate about data-driven decision making.	Cosic et. al., 2015/question Davenport & Harris, 2007/concept	Article used - "ability of senior managers to infuse a passion for BA" Book used – "passionate believers in analytical and fact-based decision making.
Top Management Support	Our Board invests resources toward improving our ability to make data-driven decisions.	Davenport & Harris, 2017/concept	"...the CEO must be able to commit the necessary resources"
Top Management Support	Senior management continually works to improve employee capabilities to make data-driven decisions.	Cosic et al., 2012	"Continuous renewal of an organizations resource base and capabilities."

Technology capability. As noted in the literature review in chapter 2, Technology capabilities include data management, data quality and data integration. Data management was defined in chapter 2 as the extent to which a mechanism is in place for ensuring data used in business analytic initiatives is a fit for the business purpose and meets the information requirements of the organization. Data quality was defined in chapter 2 as the extent of the organizations efforts in ensuring information quality. The questions asked, the source and any modifications are outlined in table 5 below:

Table 5. Technology Capability Questions.

Dimension	Question	Source/Form	Modifications
Data Management	Our practice has a data management policy in place.	Davenport & Harris, 2007/concept	"Data management that defines how the right data is acquired and managed."
Data Management	Our practice has established a glossary of standard data definitions.	Ghosh & Scott, 2011/concept	"...establish practices for supporting the creation of standard data definitions and supporting those definitions."
Data Management	Individuals responsible for managing the data in our practice partner well with data users to source data needed for decision making.	Davenport et al., 2001	"...if decision makers cannot communicate their needs ... or if data administrators cannot communicate with data modelers ... the entire data to knowledge process is at risk."
Data Quality	Data provided for decision making is current (up to date).	Davenport & Harris, 2007	"Characteristics that increase the value of data – It is current"
Data Quality	Data provided for decision making is available when needed.	Davenport & Harris, 2007	"Characteristics that increase the value of data – It is available when needed."
Data Quality	Data provided for decision making is validated.	Davenport & Harris, 2007	"...must make data clean and validate it"
Data Quality	Our practice has defined roles and responsibilities for data quality management.	Raber et. al., 2012/question	Changed "processes" to "roles and responsibilities" to add clarity

Data integration was defined in chapter 2 as the extent to which data is effectively integrated. As noted in chapter 2, many articles reference the importance of data integration, however, the questions generally asked in the articles cited focused on complex data structures that were not specific to healthcare. Based on industry experience, the key systems for physician practices include their practice management system (billing system), the electronic health record (captures patient care information), the general ledger (cost information), the purchasing system (more granular cost data by vendor); patient reported outcomes (sometimes captured in a separate system from the electronic health record) and the PACS system (imaging/films of patients). As such, the question asked was "How integrated are applications typically used in your practice? The above mentioned applications were listed for their reference. The responses ranged from no integration, low integration, some integration, high integration and extended integration. Extended integration was defined as the ability to fully integrate internal as well as some external data.

People capability. People capabilities include people skills, training and change management. People capabilities was defined in chapter 2 as the extent to which individuals in the organization have analytic skills as well as the extent of those skills. Training was defined in chapter 2 as the extent to which opportunities exist within the organization to develop analytic talent. Change management was defined in chapter 2 as the extent to which management is effective in garnering acceptance for the use of analytics to drive decision making and implementing change as a result. The questions asked, the source and any modifications are outlined in table 6 below:

Table 6. People Capability Questions.

Dimension	Question	Source/Form	Modifications
People Skills	Our practice employs dedicated decision-support analysts.	Foshay & Kuziemsky, 2013/concept	"...dedicated decision support roles"
People Skills	Our practice has a centralized business analytics department that serves all business analytic needs of the organization.	Davenport & Harris, 2007/concept	"...centralized; highly elite skilled."
People Skills	Job descriptions for management include data-driven decision making responsibilities.	Foshay & Kuziemsky, 2013/concept	"...job descriptions contain explicit decision support responsibilities."
Training	Management receives information and/or training on the appropriate use of analytics to make data-driven decisions.	Cosic et. al., 2015/Question	"...provide training to people impacted by business analytic initiatives."
Training	Employees receive information/training on the appropriate use of analytics to make data-driven decisions in their day-to-day jobs.	Cosic et al., 2015/Question	"...provide training to people impacted by business analytic initiatives."
Training	Physicians receive information/training on the benefits of analytics to improve patient care.	Cosic et al., 2015/Question	"...provide training to people impacted by business analytic initiatives."
Change Management	When implementing change in our organization, our practice sets expectations in terms of measurable outcomes.	Cosic et al., 2012/concept	"...to demonstrate the value and utility of new practices resulting from change, in order to encourage people to adopt them in their daily work."
Change Management	When implementing change in our organization, our practice communicates the business case for change.	Cosic et al., 2012/concept	"...to manage people who are impacted by BA initiatives to accept and embrace technological and process changes."
Change Management	In our practice, senior management are held accountable for achieving measurable outcomes.	Davenport & Harris, 2007/concept	"...nonperformers shouldn't be strung along for long periods."
Change Management	In our practice, department managers are held accountable for achieving measurable outcomes.	Davenport & Harris, 2007/concept	"...nonperformers shouldn't be strung along for long periods."
Change Management	In our practice, physicians are held accountable for achieving measurable outcomes.	Davenport & Harris, 2007/concept	"...nonperformers shouldn't be strung along for long periods."

Usability

As noted in the literature review, usability was defined as the extent to which analytics are visualized and reported in a manner that is accessible and easy to use for decision making. The following three questions were asked in order to obtain a measure of usability:

1. Our practice uses data visualization technologies to display output information in a format readily understood by users (physicians, management and staff).
2. Analytics used for decision making are automatically available.
3. Real-time analytics are available to all users across the practice. Real-time analytics are analytics delivered to the end user as soon as the data is captured.

The first question was the culmination of several research articles that discussed the importance of visualization of data and formatting data in way that users can easily understand. These articles were referenced in Chapter 2. The other two questions are intended to determine the accessibility of the analytics to users across the organization when they need it; this was also discussed in multiple articles which were outlined in Chapter 2.

Use of Analytics

As noted in the literature review, the use of analytics was separated into two types of use: depth of use and breadth of use. Depth of use was defined as the depth of the insights sought from performance drivers through the use of data (Davenport & Harris, 2007; Isik et al., 2013). The questions used to measure the depth of use were as follows and other than the opening line, were taken verbatim from Davenport & Harris, 2007:

1. Our practice uses business analytics to help answer the following questions: What is happening?
2. Why is this happening?
3. What if this trend continues?
4. What will happen next?
5. What is the best that can happen?

The breadth of use for purposes of this study was defined as the use of analytics for data-driven decisions across a broad spectrum of performance drivers. The questions formed simply asked if the practice was using analytics to improve financial operations, clinic workflow, patient experience, patient reported outcomes, market share, and strategic direction. The performance areas utilized in the questions came from personal industry experience as well as discussions with other executives in the industry.

Summary

This chapter provides an important bridge between the literature review and the methods used to explore the research questions outlined in chapter one. The literature review discussed in chapter two provided the building blocks from which the research model and the survey instrument were derived. In addition to the literature review, the questions and the constructs they were intended to measure were reviewed by four industry experts and four academic advisors in multiple iterations. The purpose of the review was to determine if the questions adequately measured the constructs developed and whether or not the questions would be understood by the population being surveyed. Feedback from the experts and advisors was incorporated into the questions noted above. The next chapter, describes the methodology used in this study.

CHAPTER FOUR:

METHODOLOGY

The purpose of this study was to explore the following questions: how do we measure business analytic capability maturity in the healthcare sector; what are the benefits in terms of outcomes for physician practices that are more mature in their business analytic capability; and how are physician practices improving their business analytic capabilities. This chapter outlines the research design and methods used to conduct the study. The chapter begins by describing the participants of the study and the human subjects considerations made in advance of conducting the study. It also addresses the method for administering the survey and the biases that are common in survey research. Then, the constructs are described including the measurement technique used. Finally, the research design is outlined along with a detailed description of the procedures performed.

Participants and Administration of Survey

The unit of analysis for this study was physician practices specializing in orthopaedics. The survey questions were directed toward understanding capabilities, outcomes and other characteristics of the organizations. The preferred observational unit for this survey was determined as the Chief Executive Officer (CEO) (sometimes referred to as the Practice Administrator or Chief Administrative Officer) as this individual would have the most knowledge of the various aspects of the practice this study was seeking to understand. If for some reason, the CEO was not able to answer the survey or their contact information was not attainable; the organization's Chief Financial Officer (CFO), Chief Operating Officer (COO) or Chief Information Officer were deemed appropriate substitutes.

The survey was emailed to 92 C-suite executives of physician practices who are members of a national trade-organization of orthopaedic physician practices. The trade group was used as a convenience sample as the researcher had access to this group through her role as CFO for a physician practice member of the trade organization. The trade-organization from which the participants were drawn represent the largest privately-held physician practices specializing in orthopaedics in the United States. As such, no practices with less than ten physicians were surveyed. The trade-organization's purpose is to advance each organization through benchmarking, innovation and networking. As a result of using this convenience sample, the sample chosen may not be representative of the population as a whole and represents a limitation in the research.

Due to the fact that human subjects were going to be involved in conducting the research study, the research protocol was submitted to the USF IRB. The IRB submission requested a waiver of informed consent for the study as the study design involved an anonymous survey and the research presented no more than a minimal risk of harm to subjects and involved no procedures for which written consent is normally required outside of the research context. The IRB approved the exempt determination. While a written consent was not required, an informed consent as part of the body of the email to each of the research subjects was provided.

As noted in chapter four, the survey was designed as a self-administered e-mail survey through web based software, Qualtrics. This form of survey was selected for its ease of delivery, convenience to respondents and low-cost. As noted in his book, *Social Science Research; Principles, Methods and Practices,* Dr. Anol Bhattacherjee notes that survey research is generally notorious for is low response rates. This can lead to a concern termed – non-response bias. He goes on to suggest several strategies for improving response rates several of which were employed in this research study. First, a short email was sent from the researcher to the participants soliciting them to participate in an upcoming survey. This email described briefly the purpose of the study and its importance to the physician practice community. In addition, the email committed to providing all practices with a summary of the results of the survey as a non-monetary incentive. A second email was sent along with the survey link and included an informed consent indicating the survey would be administered such that the results would be anonymous even to the researcher. Three reminder emails were sent several weeks apart to those that had not responded to encourage participation. The reminder emails were handled through Qualtrics such that the respondents and those who had not responded remained anonymous.

Other biases that exist in survey research that are relevant to this study are social desirability bias and recall bias. According to Bhattacherjee, there is practically no way of overcoming the social desirability bias in a questionnaire survey. While the results were anonymous, a few of the practice leaders know me and work with me and my practice in other contexts. This could have created social desirability bias in the responses to the questions. As it relates to recall bias, the outcomes questions in the survey do require the respondent to recall what has transpired over the past two years.

In addition, in terms of analyzing improvement over time, the respondent is asked to recall their capabilities over the past two years. The remainder of the questions ask information as of the time of the survey.

Of the 92 survey's sent, three bounced back and a substitute C-suite executive was not located. As a result, the survey was delivered to 89 C-suite executive's representing 89 different organizations. Fully completed responses were received from 32 executives for a response rate of 36%. One partial response was received but was not utilized in the data analysis or results. Of the 32 respondents, 28 were CEOs (or similar title), 3 CFO's, 1 COO. The practices were from 20 different states within the United States. The smallest practice was made up of 14 physicians and the largest practice had 120 physicians. The average number of physicians in the practices surveyed was 34.

Data Preparation

The questionnaire responses were downloaded from Qualitrics, the software used to administer the questionnaire, into an excel spreadsheet. The software assigned numbers for each of the response types, where feasible. For some of the demographic questions asked; the information downloaded was the actual response rather than a number representing the response. Some preparation of the data was required for purposes of the data analysis and testing of the hypotheses. The following steps were taken to transform and/or code the data. All data transformations were conducted in excel after downloading the responses from the Qualtrics software.

Business Performance Responses

The questions surrounding business performance were structured as follows: *In the last two years, our practice's* <outcome to be measured> *has: increased, not changed, decreased, or unsure.* The Qualtrics software structured the responses to the questions as follows: 1 = increased, 2= not changed; 3 = decreased, and 4 = unsure. The data required two transformations; the first was to reverse the format of the coding such that an answer of "increased" would receive the highest value. The second transformation was to identify any responses of "unsure" as missing data. If the entity was unsure of how their outcomes had changed over the past two years, then the response was deemed as unmeasured. This produced some missing values in the outcomes data associated patient satisfaction, market share and quality improvement. For any hypothesis testing consisting of a variable with missing values, this caused the sample size to shrink as all the responses from a respondent with missing values in a variable were removed from the analysis. The data transformation produced the following ordinal equivalents for the outcome responses captured (See Table 7 below).

Table 7. Ordinal Response Equivalents.

Response	Score	Rationale
Increased	3	Performance is improving
Not changed	2	Performance is stable
Decreased	1	Performance in declining
Not Sure	blank	Performance is not known

Maturity Capability Responses

The maturity capability questions were developed through an extensive literature review as noted in chapter three for each of the three major dimensions: organizational capabilities (OC), technology capabilities (TC) and people capabilities (PC). In total, twenty-five (25) questions were created to measure overall maturity; six (6) questions were developed to measure OC, eight (8) were developed to measure TC, and eleven (11) questions were developed to measure PC. The responses were measured by using a five-point Likert scale. Depending on the question, the requested responses were structured as a range from strongly disagree to strongly agree or never to always. The Qualtrics software automatically assigned ordinal equivalents to each of the responses as follows: 1= strongly disagree/never, 2= disagree/sometimes, 3 = neither agree nor disagree/about half the time, 4 = agree/most of the time and 5 = strongly agree/always.

In order to determine a maturity score for each of the major capabilities; the ordinal equivalents for each response to a question in a major capability area were summed and then divided by the total number of questions asked in the survey to measure that capability. For example, six questions were asked in order to measure organizational capability. The sum of the ordinal equivalents for each of the six questions were added together and then divided by six (the number of questions) in order to get an overall OC score. In order to measure business analytics capability maturity, the scores from each of the major dimensions (OC, TC, and PC) were summed.

Maturity Improvement

While hypothesis were not proposed for maturity improvement, one of the research questions was to explore how physician practices were improving their business analytic capabilities. As such, for each maturity capability question, the respondents were asked to answer the same question thinking back two years ago. Descriptive statistics were used to provide information on how practices were improving their capabilities.   Maturity improvement was measured in the same manner as the Maturity Capability Responses were measured enabling comparisons to be made between an organization's maturity today and two years prior.

Usability

Usability of business analytics describes the ease and availability of analytics across the organization. Usability was measured by asking three survey questions as outlined in chapter three. The responses were measured by using a five-point Likert scale. The requested responses were structured as a range from never to always.   The Qualtrics software automatically assigned ordinal equivalents to each of the responses as follows: 1= never, 2= sometimes, 3 = about half the time, 4 = most of the time and 5 = always.   Total usability was the sum of the ordinal equivalent for each of the three questions.

Use of Analytics

Two constructs were measured to assess the use of analytics: depth of use and breadth of use. These were developed through an extensive literature review as discussed in chapter three. Depth of use is defined as the depth of the insights sought regarding performance drivers through the use of the data (Davenport & Harris, 2007). A low maturity organization would seek insights to describe what is happening while a highly competitive organization would seek insights to describe the best that could happen (Davenport & Harris, 2007).   Breadth of use is defined as the use of analytics for data-driven decisions across a broad spectrum of performance drivers.

The responses were measured by using a five-point Likert scale ranging from never to always. The Qualtrics software automatically assigned ordinal equivalents to each of the responses as follows: 1= never, 2= sometimes, 3 = about half the time, 4 = most of the time and 5 = always. Total depth of use was measured as the sum of the ordinal equivalent for each response to the five questions asked, as outlined in chapter three. Breadth of use was measured as the sum of the ordinal equivalent for each response to the six questions asked; as outlined in chapter three.

Research Design

The purpose of the study was to answer the three research questions (RQ) outlined at the beginning of this chapter. The research design varies for each of the questions and as such, each are discussed independently.

RQ1: Measuring a Business Analytic Capability

The first research question was: How do we measure business analytic capability maturity in the healthcare sector and more specifically in physician practices? In order to answer this question, an extensive literature review was conducted and is detailed in chapters two and three. The literature review sought peer reviewed and well cited industry articles using the search terms identified in Appendix A which included business analytics in healthcare and business intelligence in healthcare. The articles were filtered for peer-reviewed articles and sorted by the most relevant. The top twenty articles for each term searched were selected for an in-depth review. Articles dismissed included those that were not highly cited and those that upon a cursory review did not pertain directly to the topic of interest. Of the articles searched, 44 articles were used in the analysis; some of those articles referenced other papers of interest which were also reviewed.

In phase one of the literature review, constructs were developed and defined. These constructs were reviewed by four industry experts and four academic advisors to assess how completely the subject matter had been assessed and whether or not the definitions adequately described what was to be measured. In the second phase of the literature review, questions were developed for the survey that attempted to measure the constructs that had been defined. The questions were also reviewed by four industry experts and four academic advisors. The reviews were conducted to ensure the questions were good translations of the constructs being measured and that any poorly worded or ambiguous questions were modified. They were also reviewed to ensure the questions were worded in a way that would make sense to the population being surveyed. These reviews were conducted multiple times until consensus was reached. Adjustments were made in both phases based on the feedback received. As a result of this process, the survey instrument designed achieved the following types of validity:

- Face validity – The questions are a reasonable way to obtain the results.
- Content validity – The questions reflect the issues being researched and cover constructs derived from the literature review.
- Internal validity – The questions explain the constructs we are trying to measure.
- External validity – The questions are written in a way the population being surveyed can understand and relate to.

In addition, the survey results were tested for reliability. The reliability test ensures the results obtained are accurate and repeatable (DeBruin et al., 2005). Reliability was tested using the Cronbach's Alpha method. The constructs measured in the survey along with some descriptive statistics are presented in Table 8 below.

Table 8. Descriptive Statistics of Research Constructs.

Constructs	# of Items	Cronbach Alpha	Mean	Std. Deviation
Organizational Capability (OC)	6	.734	4.109	0.561
Technology Capability (TC)	8	.861	3.746	0.709
People Capability (PC)	11	.891	3.341	0.774
Business Analytic Maturity (MAT)	3	.867	11.196	1.832
Usability (UBLTY)	3	.789	9.313	2.977
Depth of Use (USE_D)	5	.937	17.063	5.001
Breadth of Use (USE_B)	6	.853	20.000	4.938

RQ2: Maturity Benefits

The second research question was: What are the benefits in terms of outcomes for physician practices that are more mature in their business analytic capability? Based on the literature review and industry experience, a conceptual research model was proposed along with supporting hypotheses. The conceptual model and hypotheses were introduced in chapter 3 and the research design for each hypotheses is discussed below.

Hypothesis one. The first hypothesis proposes that the greater the business analytic capability, the more likely that business analytics will be used in decision making and that the usability of the data will have a moderating effect. The hypotheses introduced in chapter 4 were as follows:

H1a: Business analytics capability maturity is positively correlated with depth of use of analytics.
H1b: Business analytics capability maturity is positively correlated with breadth of use of analytics.
H1c: Usability of analytics together with business analytics capability maturity has a positive impact on the depth of use.
H1d: Usability of analytics together with business analytics capability maturity has a positive impact on the breadth of use.

The dependent variable for H1a was the depth of use of analytics (USE_D) while the dependent variable for H1b was the breadth of use of analytics (USE_B). The independent variables used are business analytic capability maturity (MAT) and usability of analytics (UBLTY).

Hypotheses two. The second series of hypotheses proposes that the use of analytics to drive business decisions improves financial performance. The four hypotheses introduced in chapter 4 follow:

H2a: Depth of use of analytics is positively correlated with improved financial performance as measured by patient revenues.
H2b: Breadth of use of analytics is positively correlated with improved financial performance as measured by patient revenues.
H2c: Depth of use of analytics is positively correlated with improved financial performance as measured by average physician compensation.
H2d: Breadth of use of analytics is positively correlated with improved financial performance as measured by average physician compensation.

The dependent variable for H2a and H2b is the financial performance as measured by patient revenues (FP_R) while the dependent variable for H2c and H2d is the financial performance as measured by average physician compensation (FP_C). The independent variables for each are depth of use of analytics (USE_D) and breadth of use of analytics (USE_B). There were no missing data for these variables; the number of respondents to the survey was 32.

Hypotheses three. The third series of hypotheses proposes that the use of analytics to drive business decisions improves patient satisfaction. The two hypotheses introduced in chapter 4 were as follows:

H3a: Depth of use of analytics is positively correlated with improved patient satisfaction.
H3b: Breadth of use of analytics is positively correlated with improved patient satisfaction.

The dependent variable for H3a and H3b is the patient satisfaction (PS). The independent variables for each are depth of use of analytics (USE_D) and breadth of use of analytics (USE_B). Seven (7) of the practices responded that they were unsure of their patient satisfaction performance over the past two years. As such, those practices' data were excluded automatically by the statistical software, SPSS, in the analysis. While the overall respondents to the survey was 32, for purposes of this hypotheses, only 27 responses were utilized.

Hypotheses four. The fourth series of hypotheses proposes that the use of analytics to drive business decisions improves market share. The two hypotheses introduced in chapter4 were as follows:

H4a: Depth of use of analytics is positively correlated with improved market share.
H4b: Breadth of use of analytics is positively correlated with improved market share

The dependent variable for H4a and H4b is the practice's market share performance (M_SH). The independent variables for each are depth of use of analytics (USE_D) and breadth of use of analytics (USE_B). Three (3) of the practices responded that they were unsure of their market share performance over the past two years. As such, those practices' data were excluded automatically by SPSS in the analysis. While the overall respondents to the survey was 32, for purposes of this hypotheses, only 29 responses were analyzed.

Hypotheses five. The fifth series of hypotheses proposes that the use of analytics to drive business decisions improves quality of care. The two hypotheses introduced in chapter 4 were as follows:

H5a: Depth of use of analytics is positively correlated with improved quality of care.
H5b: Breadth of use of analytics is positively correlated with improved quality of care.

The dependent variable for H5a and H5b is the practice's quality of care performance (QI). The independent variables for each are depth of use of analytics (USE_D) and breadth of use of analytics (USE_B). Twelve (12) of the practices responded that they were unsure of their quality of care performance over the past two years. As such, those practices data were excluded automatically by SPSS in the analysis. While the overall respondents to the survey was 32, for purposes of this hypotheses, only 20 responses were analyzed.

Data analysis. In order to examine the research model and resulting hypotheses, linear regression was conducted to investigate whether or not the independent variables identified were positively correlated with the dependent variables identified. The software SPSS was used for all statistical analysis.

In order to test all the hypotheses noted above, linear regression was run in SPSS along with a scatterplot of residuals on the Y axis and predicted values along the X axis. This scatter plot was used to test the homoscedasticity and linearity assumptions. Additionally, as part of this linear regression analysis, SPSS captured the unstandardized residuals as a separate variable. The creation of this variable enabled the Shapiro Wilks analysis to be performed which examines whether or not the dependent variable is normally distributed. As long as all assumptions of linear regression were met, no further analysis was required. In situations where the dependent variable was not normally distributed, a review was conducted to determine whether or not the data could be transformed or a nonparametric regression method could be employed. If neither were feasible or would produce greater statistical power, then a more conservative p-value of .01, rather than .05, was used for interpreting correlation significance.

RQ 3: Improving Business Analytic Capability

The third research question was: How are physician practices improving their business analytic capabilities? For this research questions, our survey of the 92 physician practices requested responses to each maturity capability question in terms of today (the present) and two years ago (the recent past). The constructs used to explore this research questions include business analytic capability maturity (MAT), organizational capability (OC), technology capability (TC) and people capability (PC) as of today and as of two years ago (past): MAT_P, OC_P, TC_P and PC_P. In order to analyze the results, the scores were assessed and populated into the levels of maturity identified in Chapter 2. The results of the exploratory analysis was conducted to inform practice.

Summary

The research methodology for the first research questions consisted of a comprehensive literature review and the creation of a survey instrument. This survey instrument was completed by 32 CEO's of physician practices specializing in orthopaedics in the United States. The results of the survey along with the research methodologies described above were utilized to explore the second and third research questions. The next chapter discusses the results of the research.

CHAPTER FIVE:

FINDINGS

As outlined in chapter one, this research paper seeks to explore the following research questions:

1. How do we measure business analytic capability maturity in the healthcare sector and more specifically, in physician practices?
2. What are the benefits in terms of outcomes for physician practices that are more mature in their business analytic capability?
3. How are physician practices improving their business analytic capabilities?

The first research question was answered through an extensive review of the research literature and is described in chapter three. Chapters three and four build on each other and develop the formation of the hypotheses that seek to answer the second research question noted above. The results from testing the hypotheses are presented here in the findings. Finally, the third research question is explored at the end of this chapter through descriptive statistics derived from the survey results.

Hypotheses one

As noted in chapter four, a business analytic capability maturity drives the use of analytics in decision making. In addition, we identified in our research that the usability of analytics also has an impact on the use of analytics in decision making. In our research model and hypotheses we proposed that usability together with a business analytics capability maturity has a positive effect on both the depth and breadth of use of analytics. The hypotheses proposed were as follows:

H1a: Business analytics capability maturity is positively correlated with depth of use of analytics.
H1b: Business analytics capability maturity is positively correlated with breadth of use of analytics.
H1c: Usability of analytics together with business analytics capability maturity has a positive impact on the depth of use.
H1d: Usability of analytics together with business analytics capability maturity has a positive impact on the breadth of use.

For hypotheses 1, linear regression analysis was conducted in SPSS. For hypotheses 1a and 1c, depth of use (USE_D) was input as the dependent variable and business analytic capability maturity (MAT) and usability (UBLTY) were input as independent variables. For hypotheses 1b and 1d, breadth of use (USE_B) was input as the dependent variable and MAT and UBLTY were input as independent variables. Table 9, below, identifies the results of the linear regression.

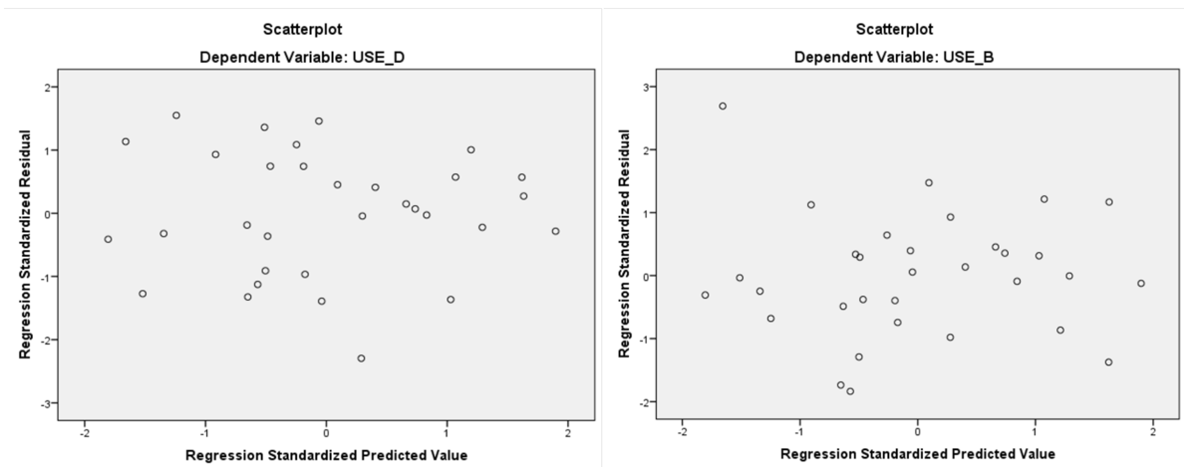
Table 9. Results of Hypothesis 1a – 1d.

Model	F-Test	R Square	Unstandardized Coefficients		t-statistic
			B	Std. Error	
H1a & H1c					
DV: USE_D	16.584****	0.534			
IV: MAT			1.412	0.427	3.311***
IV: USBLTY			0.499	0.262	1.902*
H1b & H1d					
DV: USE_B	23.832****	0.622			
IV: MAT			1.483	0.379	3.917****
IV: USBLTY			0.545	0.233	2.339**
****p<.001; ***p<.01; **p<.05; *p<.10					

The assumptions for linear regression; linearity, normality and homoscedasticity were assessed. Linearity and homoscedasticity were analyzed using scatterplots of residuals on the Y axis and predicted values along the X axis as noted in Table 10 below. The scatterplots indicate the two assumptions were met as the plots formed no real pattern and the range of predicted values were fairly evenly distributed along the mean residual of zero.

Table 10. Linearity and Homoscedasticity Assumptions H1a-H1d

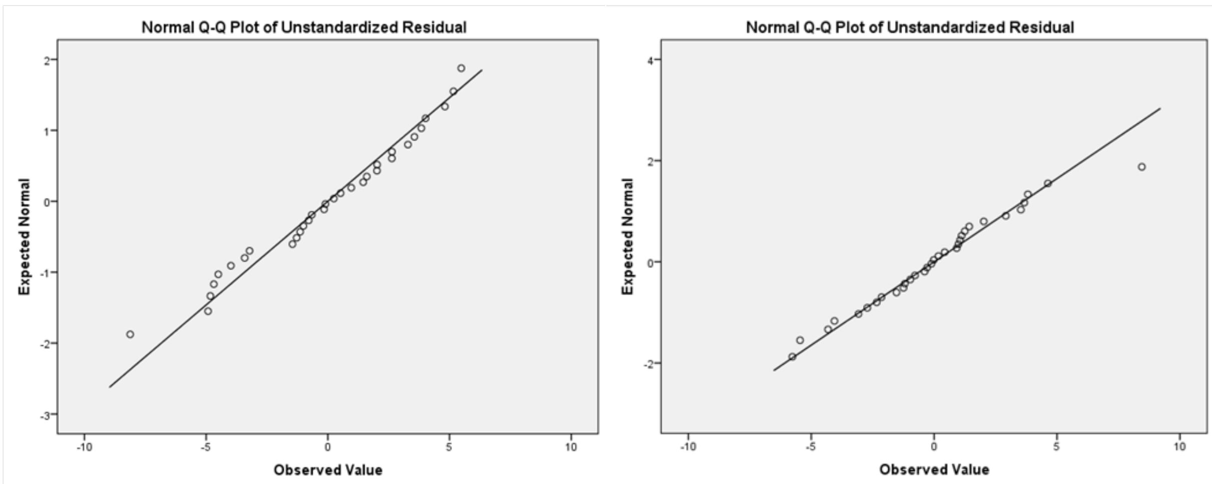
Linearity and Homoscedasticity



The Shapiro-Wilk (S-W) test was run to test normality along with a normal Q-Q plot of unstandardized residuals (see Table 11 below). Based on the results of the test, the p-value of .464 (DV: USE_D) and a p-value of .736 (DV: USE_B) would indicate the null hypotheses (data tested are from a normally distributed population) cannot be rejected. In addition, the Q-Q plots shows the plotted values are closely aligned with the straight line. The assumptions for linear regression for these regression models were met.

Table 11. Normality Assumptions H1a-H1d

Normality (DV: USE_D on left – DV: USE_B on right)



In summary, maturity is positively correlated with depth of use at a 95% confidence level while usability of analytics is also correlated with depth of use but at a 90% confidence level. Overall, the model explains 53.4% of the overall variability in the organizations' depth of use of analytics. Maturity and usability of analytics are positively correlated with breadth of use at a 95% confidence level. Overall, the model explains 62.2% of the overall variability in the organizations' depth of use of analytics.

Other Analyses

In addition to the two hypotheses tested above, we also explored whether or not the individual capabilities (Organizational Capability (OC), Technology Capability (TC) and People Capability (PC)) were positively correlated with depth of use or breadth of use. Table 12 indicates the results of the analyses.

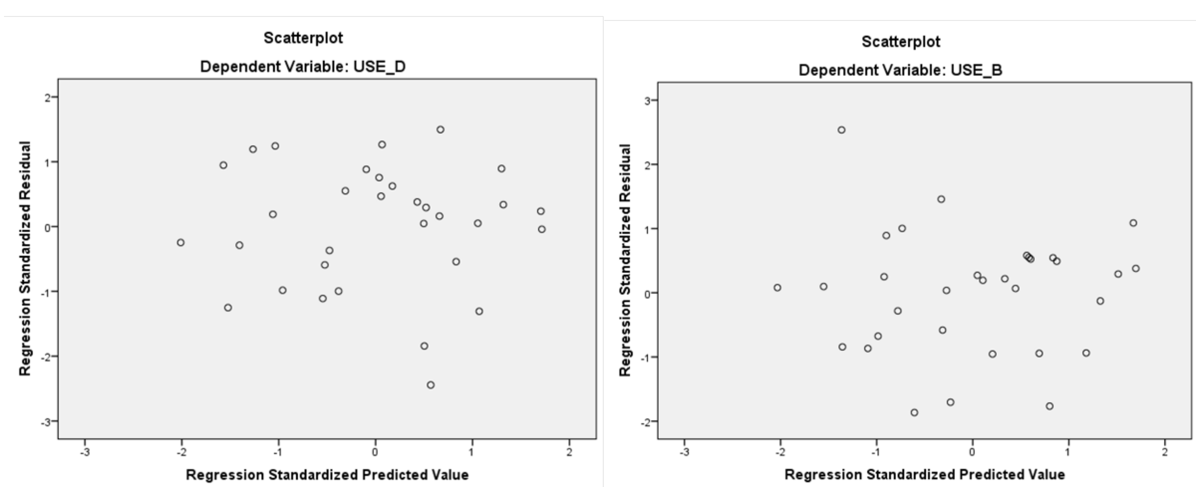
Table 12. Results of Other Analysis of Depth and Breadth of Use of Analytics.

Model	F-Test	R Square	Unstandardized Coefficients		t-statistic
			B	Std. Error	
Other Analysis 1a					
DV: USE_D	9.443****	0.503			
IV: OC			-0.33	1.83	-0.18
IV: TC			2.875	1.624	1.771*
IV: PC			2.498	1.275	1.960*
Other Analysis 1b					
DV: USE_B	19.248****	0.673			
IV: OC			-1.858	1.463	-1.27
IV: TC			2.276	1.297	1.754*
IV: PC			4.43	1.019	4.349****
****p<.001; ***p<.01; **p<.05; *p<.10					

The assumptions for linear regression; linearity, normality and homoscedasticity were assessed. Linearity and homoscedasticity were analyzed using scatterplots of residuals on the Y axis and predicted values along the X axis as noted in Table 13 below. The scatterplots indicate the two assumptions were met as the plots formed no real pattern and the range of predicted values were fairly evenly distributed along the mean residual of zero.

Table 13. Linearity and Homoscedasticity Assumptions (Other analysis 1a and 1b)

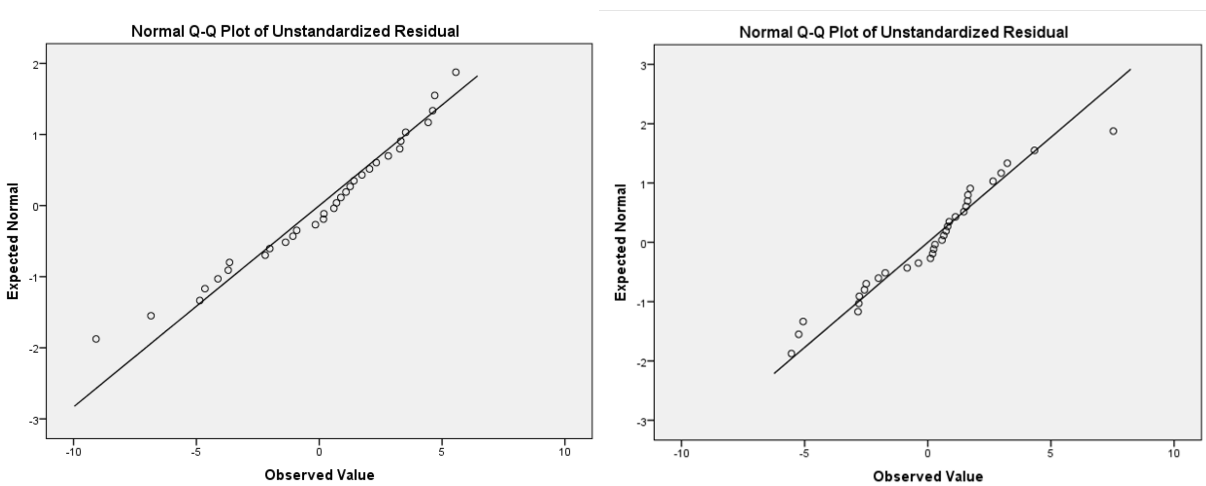
Linearity and Homoscedasticity



The Shapiro-Wilk (S-W) test was run to test normality along with a normal Q-Q plot of unstandardized residuals (see Table 14 below). Based on the results of the test, the p-values of .309 (other analysis 1a) and .304 (other analysis 1b) would indicate the null hypotheses (data tested are from a normally distributed population) cannot be rejected. In addition, the Q-Q plots shows the plotted values are closely aligned with the straight line. The assumptions for linear regression for these regression models were met.

Table 14. Normality Assumptions (Other analysis 1a and 1b)

Normality (DV: USE_D on left – DV: USE_B on right)



In summary, technology capabilities and people capabilities were found to be positively correlated with the depth of use of analytics at a 90% confidence level and they were both positively correlated with breadth of use of analytics at a 90% and 99% confidence level, respectively. Interestingly, organizational capabilities were not found to be significantly correlated to depth or breadth of use. Organizational capabilities were measured by asking questions around top management support and the linkages between strategy and business analytics. These concepts are difficult to measure as they are more complex than the other more objective measures in the survey. In addition, these measures may be subject to greater social desirability bias as the all the questions were asked of CEO's of the organizations. CEO's drive top management support and are responsible for the business strategy. This is an area future research will need to explore.

Hypotheses two through five

We have now shown that a capability maturity along with usability of the analytics is positively correlated with the depth and breadth of use of analytics. As discussed in chapter three, the conceptual model developed proposes that the use of analytics (depth and breadth) are positively correlated with financial performance (of which we measured two areas), patient satisfaction, market share, and quality outcomes. Each of the hypotheses are listed in Table 15 on the next page.

For each of these hypotheses listed, linear regression analysis was conducted in SPSS. The independent variables for all of these hypotheses were the depth of use (USE_D) and breadth of use (USE_B). The independent variables for each of the hypotheses are listed in Table 15.

The assumptions for linear regression; linearity, normality and homoscedasticity were also assessed for each hypotheses. Linearity and homoscedasticity were analyzed using scatterplots of residuals on the Y axis and predicted values along the X axis. The Shapiro-Wilk (S-W) test was run to test normality. Based on the results of test, normality of the dependent variable was not present in any of the hypotheses. While normality was not met, linear regression is known to be robust for validity even in the absence of normality; it just may not be the most powerful test available. In addition, the small sample size of 32 also has an effect on the power of this test. While transformation of the data was considered, the sample size was too small to conduct the relevant non-parametric tests. As such, linear regression was considered reliable at a more conservative p-value of less than .01 for conducting significance tests. The results of the linear regression are shown in Table 16.

Table 15. Hypotheses 2, 3, 4 and 5.

Hypotheses 2:	Dependent variables are financial outcomes as measured by patient revenues (FP_R) in H2a and H2b and financial outcomes as measured by average physician compensation (FP-C) in H2c and H2d.
H2a.	USE_D is positively correlated with FP_R
H2b.	USE_B is positively correlated with FP_R
H2c.	USE_D is positively correlated with FP_C
H2d.	USE_B is positively correlated with FP_C
Hypotheses 3:	Dependent variable is patient satisfaction (PS)
H3a.	USE_D is positively correlated with PS
H3b.	USE_B is positively correlated with PS
Hypotheses 4:	Dependent variable is market share (M_SH)
H4a.	USE_D is positively correlated with M_SH
H4b.	USE_B is positively correlated with M_SH
Hypotheses 5:	Dependent variable is quality outcomes (QI)
H5a.	USE_D is positively correlated with QI
H5b.	USE_B is positively correlated with QI

Table 16. Results of hypotheses 2a – 2d, 3a & 3b, 4a & 4b and 5a & 5b.

Outcome Models	F-Test	R Square	Unstandardized Coefficients		t-statistic
			B	Std. Error	
Model H2a&b					
DV: FP_R	1.75	0.108			
IV: USE_D			0.056	0.039	1.457
IV: USE_B			-0.007	0.039	-0.172
Model H2c&d					
DV: FP_C	1.844	0.113			
IV: USE_D			-0.002	0.039	-0.05
IV: USE_B			0.056	0.039	1.413
Model H3a&b					
DV: PS	0.056	0.005			
IV: USE_D			0.001	0.029	0.018
IV: USE_B			-0.009	0.031	-0.283
Model H4a&b					
DV: M_SH	3.412**	0.208			
IV: USE_D			0.023	0.029	0.805
IV: USE_B			0.038	0.03	1.291
Model H5a&b					
DV: QI	1.578	0.157			
IV: USE_D			0.045	0.028	1.614
IV: USE_B			0.004	0.034	0.108
****p<.001; ***p<.01; **p<.05; *p<.10					

In summary, the linear regression showed no correlation between the depth use of analytics and the breadth of use of analytics with any of the outcome measures (the dependent variables). As a result, the hypotheses noted above were rejected. This may be due in part to the way the study attempted to measure these outcomes. As mentioned in chapter three, actual outcomes were not captured. Instead, the survey questions asked whether or not the organization's outcome performance had improved, stayed the same, or decreased over the past two years; it also allowed a response indicating they were unsure. This creates some level of weakness in the validity of the measurement. Actual performance over time would provide a more valid and reliable measurement but was not available for this research study. This should be considered for future studies. In addition, there is lag time between the time an organization improves its capabilities and the time they begin to see results. This may have contributed to the lack of correlation noted above. Finally, for several of the outcomes, some of the practices were unsure of their results. As such, the responses from those practices were excluded from the analysis. This occurred with the following outcomes, as noted in chapter four: patient satisfaction, market share and quality outcomes. The smaller sample sizes for these outcomes may not have provided enough data points to adequately assess whether or not outcomes were correlated with use of analytics.

RQ3: Improving Business Analytic Capability

The third and final research question was: How are physician practices improving their business analytic capabilities. In order to explore this question, the survey questions intended to measure a business analytic capability requested the respondent to reply both in terms of today and in terms of their practice two years prior. The responses to the questions for both today and two years prior were placed into the maturity model using the average score for each practice based on the scale identified in Figure 3. The possible values ranged from 3 to 15. The overall business analytic maturity scores for today and two years ago ranged from 3 to 15; however, the capability dimensions (OC, TC and PC) ranged from 1 to 5. In order to place the results of the capability dimensions into the maturity model using the scale noted above; each of the practices scores in these areas were multiplied by 3.

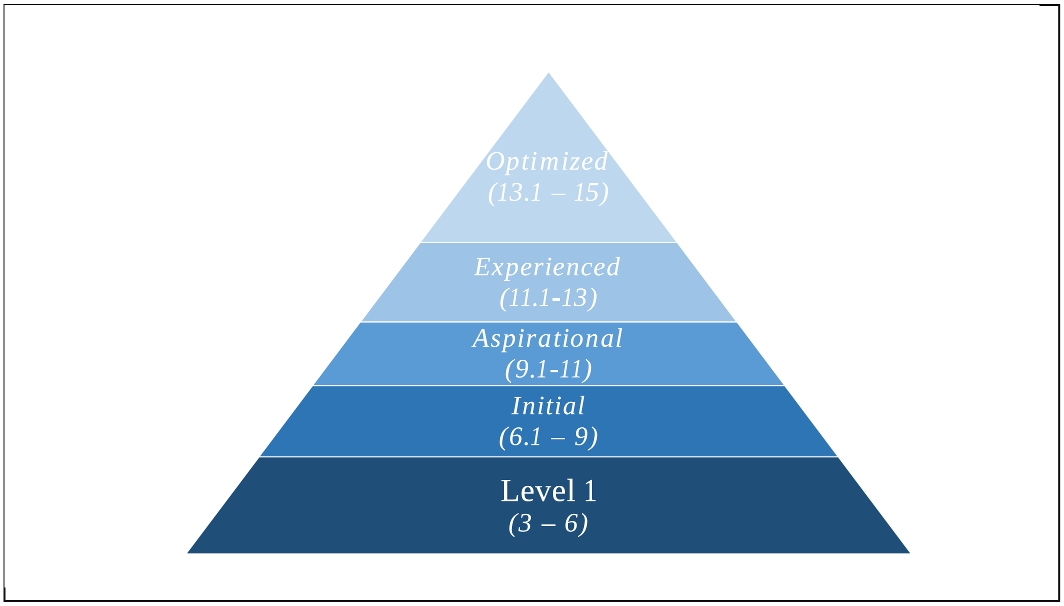


Figure 3. Business analytic maturity model with scale embedded

Based on the results of the survey and using the scale identified above, the physician practices specializing in orthopaedics who responded to the survey have been improving in their capabilities over the past two years. As noted in the Table 17 below, two years ago, a majority, or 53% of the practices surveyed, were at the non-existent or initial levels of maturity while today, a majority or 60% of the practices are experienced or optimized.

Table 17. Business Analytic Capability Maturity Today and Two Years Ago

Busiiness Analytics Capability Maturity		
% of Practices Today		% of Practices Two Years Ago
0%	Non-Existent	3%
19%	Initial	50%
22%	Aspirational	31%
44%	Experienced	16%
16%	Optimzed	0%
100%		100%

As it relates to the capability dimensions (organizational, technology and people), the results also show an improvement in capabilities in each of these dimensions from two years ago. (See Table 18) The most notable improvements occurred in the areas of technology capabilities and people capabilities. These two areas were also noted to be correlated with the use of analytics. It can also be seen from the data reported in Table 18, that the capability area which continues to need the most improvement from the majority of the respondents is in people capabilities. Both the technology capabilities and the people capabilities are areas where physician practices should focus their resources and efforts.

Table 18. Capability Dimensions Today and Two Years Ago

	Organizational Capabilities		Technology Capabilities		People Capabilities	
	% of Practices Today	% of Practices Two Years Ago	% of Practices Today	% of Practices Two Years Ago	% of Practices Today	% of Practices Two Years Ago
Non-Existent	0%	13%	0%	3%	3%	28%
Initial	3%	28%	19%	53%	38%	44%
Aspirational	22%	28%	22%	25%	19%	25%
Experienced	47%	25%	38%	9%	28%	3%
Optimzed	28%	6%	22%	9%	13%	0%
	100%	100%	100%	100%	100%	100%

Summary

This chapter walked through the results and statistical analysis, where relevant, for each of the research questions explored in this study. The results of the research question concerned with how we measure business analytic capability maturity in the healthcare sector and more specifically physician practices resulted in a survey instrument that was grounded in an extensive literature review and validated through a series of reviews conducted by industry experts and experienced academic faculty. For the second research question, we were able to show that building an organizations maturity in their business analytics capability improved both the breadth and depth of use of analytics to drive business decisions. We were not able to show that the breadth and depth of use of analytics to drive business decisions improved performance. Finally, through exploratory analysis of the results of the survey, we were able to fit each of the respondents into the maturity model and were able to compare their maturity today to their maturity two years ago. The results show that physician practices are focused on building their business analytic capabilities and have seen improvement in the past two years. The next chapter provides a high level discussion of the results, the contributions to research, the contributions to practice, and recommendations for future research.

CHAPTER SIX:

DISCUSSION

This research study explored three research questions of interest regarding business analytics. First, an extensive literature review was conducted to determine how a business in the health care industry could measure its business analytic capability. The literature review conducted revealed several key insights. First, maturity models are often cited in the literature and used in industry to assess maturity of a particular capability. These maturity models enable the industry or a particular organization with insights on where and how to improve upon their capabilities. Second, the research literature identified three major dimensions that together contribute to a business analytic capability in healthcare. The dimensions identified were:

1. Organizational Capabilities - included the extent to which business analytic initiatives were linked with strategic objectives of the organization and the extent to which top management supports business analytic initiatives.
2. Technology Capabilities – included mechanisms for ensuring that data used was a fit for the purpose, the quality of the data and the extent to which data is effectively integrated.

3. People Capabilities – included analytic skills of people in the organization, the training opportunities that exist and effectiveness of change management efforts in garnering acceptance for the use of analytics.

Based on these key insights, a survey instrument was developed to measure the capabilities and assess overall business analytic capability maturity. The survey was emailed to 89 C-suite executives of independent physician practices specializing in orthopaedics.

The next area of interest was to determine the benefits of maturing an organization's business analytic capability. The research literature provided insights to that as well and from the literature, a conceptual model was developed and several hypotheses were proposed. Through this work, we learned that maturing an organization's business analytic capability improves the organizations depth and breadth of use of analytics to drive business decisions. In addition, we learned that the usability of the data in terms of its ease of understanding and its timeliness of delivery together with a mature business analytic capability improves the organizations depth and breadth of use of analytics. Finally, we explored whether or not any of the major dimensions individually contributed to the depth and breadth of use of analytics. The analysis revealed that technology capabilities and people capabilities were correlated with the depth and breadth of use but that organizational capabilities were not correlated.

The research also explored whether or not an increase in the breadth and depth of use of analytics improved business performance however, no correlation was found. This may be due to the way in which business performance was measured. Actual business performance results over the two year period in question were not available.

Instead, our questionnaire asked C-suite executives to recall whether or not their outcomes improved. We believe that the data gathered from the survey as it relates to outcomes may have weak validity and as such, may have impacted the results. As such, we believe this area warrants additional research.

Finally, we explored the level of maturity of physician practices specializing in orthopaedics today compared with their level of maturity two years ago in order to determine how practices were improving their capabilities. The data showed that practices have improved over the past two years in all dimensions of business analytic capabilities. However, the majority of the practices surveyed continue to need development in technology capabilities and particularly in their people capabilities. These two dimensions were also noted to be correlated with the depth and breadth of use of analytics and as such, physician practices should focus their resources and efforts in these areas.

There are some limitations of this study. First, the sample size was small which influences the significance of the findings. Future research should consider expanding the population to include all independent physician practices rather than focusing on one specialty, orthopaedics. Second, there are limitations in using the survey method for this type of analysis. For instance, survey research is always susceptible to self-response bias. In the software industry, the levels of maturity are assessed using observation using a predefined set of objective metrics rather than through a self-response survey. Future research should consider whether an observational study, such as case research, which would provide a more objective assessment of analytics capability than a self-response survey.

From a research perspective, this study contributes to the research on business analytic capability maturity overall and more specifically, to the research focused on this subject for the healthcare industry. It provides additional support for those studies that have shown a correlation between a business analytic capability and the depth and breadth of use of analytics to drive business decisions. Further research is needed to understand organizational capabilities and their impact on the depth and breadth of use of analytics. In addition, further research is needed in the healthcare industry to determine whether or not the investments in data-driven decision making is yielding the expected return in terms of improved outcomes.

From a practitioner's perspective, this study outlines key dimensions practices should mature to improve their business analytics capabilities which will lead to improved depth and breadth of use of analytics. It also highlights to practitioner's the importance of focusing their efforts on the technology and people capabilities. These are the areas that were shown to be positively correlated with use and these also happen to be the areas where there is the most opportunity for improvement.

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APPENDICES

Appendix A: Literature Review Protocol

Search Methodology

The literature review search was conducted through the USF on-line Library using Google Scholar. The terms used in the search are highlighted below. The articles were filtered for peer-reviewed studies and relevance. The top twenty articles, abstracts or books reviewed from each key word search were selected for further analysis and the results are listed below. In some cases, an article was reviewed that referenced a book or article that had not come up in the key word search that appeared relevant to the research questions in the study. In those cases, the referenced article was also reviewed.

Table A1. Search Terms

Terms Used:	# of articles found
Business Analytics	377,000
Business Analytics in Healthcare	49,600
Business Analytics Capability	69,600
Business Analytics Capability in Healthcare	19,200
Business Analytics Capability Maturity Model	24,000
Business Intelligence Capability	524,000
Business Intelligence Capability Maturity Model	59,700
Business Intelligence capability in Healthcare	61,100
Business Intelligence in Healthcare	212,000

Table A2: Search Results

# of Articles or Abstracts Listed	180
# of Articles selected for more In-Depth Review	44
# of Articles dismissed	76
# of unique articles	120

Appendix B: Survey Instrument Downloaded from Qualtrics Software

Analytics in Healthcare

Thank you for taking the time to complete this survey. The following definitions should assist you as you respond to the survey questions. Business analytics - the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions. Real-time analytics - data analytics delivered to the end user as soon as the data is captured.

Q1 Which best describes your position or role at your practice?

- ❍ CEO (1)
- ❍ CFO (2)
- ❍ COO (3)
- ❍ Other, please specify (4) ____________________

Q2 How many physicians are in your practice? (MDs or DOs, only)

Q3 Please enter the number of practice locations in your practice.

Q4 Please enter the number of years your practice has been in business.

Q5 Please enter the state in which you practice is located.

Q6 In the last two years, our practice's patient revenue per physician (total patient revenue divided by the number of physicians (MD and DO only) has:

- ❍ Increased (1)
- ❍ Not changed (2)
- ❍ Decreased (3)
- ❍ Unsure (4)

Q7 In the last two years, our practice's average compensation per physician (MDs and DOs) has:

- Increased (1)
- Not changed (2)
- Decreased (3)
- Unsure (4)

Q8 In the last two years, our practice's overall patient satisfaction score has:

- Increased (1)
- Not changed (2)
- Decreased (3)
- Unsure (4)

Q9 In the last two years, our practice's overall market share in our primary service area has:

- Increased (1)
- Not changed (2)
- Decreased (3)
- Unsure (4)

Q10 In the last two years, our practice's quality outcomes have:

- Increased (1)
- Not changed (2)
- Decreased (3)
- Unsure (4)

For each of the following statements, you will be asked to respond to the statement based on what is happening in your practice today and based on what was happening in your practice two years ago.

Q11 Building and/or improving the ability to make data-driven decisions is a key part of our practice's strategy.

	Strongly Disagree (1)	Disagree (2)	Neither agree nor disagree (3)	Agree (4)	Strongly agree (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q12 Our practice's strategic initiatives are linked to measurable outcomes.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q13 Our practice predicts and prepares for the future by proactively evaluating scenarios and potential trade-offs.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q14 Members of senior management are passionate about data-driven decision making.

	Strongly Disagree (1)	Disagree (2)	Neither agree nor disagree (3)	Agree (4)	Strongly agree (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q15 Our Board invests resources toward improving our ability to make data-driven decisions.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q16 Senior management continually works to improve employee capabilities to make data-driven decisions.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q17 Management in all areas of the practice use business analytics to develop innovative and more effective processes.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q18 Physicians in all areas of our practice use analytics to improve patient care.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q19 Front-line staff in all areas of our practice use analytics to improve the patient experience.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q20 Our practice has a data management policy in place.

	Strongly disagree (1)	Disagree (2)	Neither agree nor disagree (3)	Agree (4)	Strongly agree (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q21 Our practice has established a glossary of standard data definitions.

	Strongly Disagree (1)	Disagree (2)	Neither agree nor disagree (3)	Agree (4)	Strongly agree (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q22 Individuals responsible for managing the data in our practice partner well with data users to source data needed for decision making.

	Strongly disagree (1)	Disagree (2)	Neither agree nor disagree (3)	Agree (4)	Strongly agree (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q23 Data provided for decision making is current (up to date).

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q24 Data provided for decision making is available when needed.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q25 Data provided for decision making is validated.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q26 Our practice has defined roles and responsibilities for data quality management.

	Strongly Disagree (1)	Disagree (2)	Neither agree nor disagree (3)	Agree (4)	Strongly agree (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q27 How integrated are applications typically used in your practice? Applications: Practice management system, electronic health record, general ledger, purchasing system, patient reported outcomes, PACS system.

	No integration (numerous disconnected applications) (1)	Low integration (some progress towards integrating applications) (2)	Some integration (3 to 4 applications are integrated) (3)	High integration (ability to integrate (4)	Extended Integration (ability to fully integrate internal and some external data (hospital, ASC, skilled nursing, etc.) (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q28 Our practice employs dedicated decision-support analysts.

	Strongly disagree (1)	Disagree (2)	Neither agree nor disagree (3)	Agree (4)	Strongly agree (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q29 Our practice has a centralized business analytics department that serves all business analytics needs of the organization.

	Strongly Disagree (1)	Disagree (2)	Neither agree nor disagree (3)	Agree (4)	Strongly agree (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q30 Job descriptions for management include data-driven decision making responsibilities.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q31 Management receives information and/or training on the appropriate use of analytics to make data-driven decisions.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q32 Employees receive information/training on the appropriate use of analytics to make data-driven decisions in their day to day jobs.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q33 Physicians receive information/training on the benefits of analytics to improve patient care.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q34 When implementing change in our organization, our practice sets expectations in terms of measurable outcomes.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q35 When implementing change in our organization, our practice communicates the business case for change.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q36 In our practice, senior management are held accountable for achieving measurable outcomes.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q37 In our practice, department managers are held accountable for achieving measurable outcomes.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q38 In our practice, physicians are held accountable for achieving measurable outcomes .

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q39 Our practice uses data visualization technologies to display output information in a format readily understood by users (physicians, management and staff).

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q40 Analytics used for decision making are automatically available.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q41 Real-time analytics are available to all users across the practice. Real-time analytics - analytics delivered to the end user as soon as the data is captured.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q42 Our practice uses business analytics to help answer the following questions: Today:

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
What is happening? (1)	❍	❍	❍	❍	❍
Why is this happening? (2)	❍	❍	❍	❍	❍
What if this trend continues? (3)	❍	❍	❍	❍	❍
What will happen next? (4)	❍	❍	❍	❍	❍
What is the best that can happen? (5)	❍	❍	❍	❍	❍

Two years ago:

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
What is happening? (1)	❍	❍	❍	❍	❍
Why is this happening? (2)	❍	❍	❍	❍	❍
What if this trend continues? (3)	❍	❍	❍	❍	❍
What will happen next? (4)	❍	❍	❍	❍	❍
What is the best that can happen? (5)	❍	❍	❍	❍	❍

Q43 Our practice uses business analytics to improve financial operations.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q44 Our practice uses business analytics to improve clinic workflow.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q45 Our practice uses business analytics to improve patient experience.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q46 Our practice uses business analytics to improve patient reported outcomes.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q47 Our practice uses business analytics to improve our market share.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

Q48 Our practice uses business analytics to establish our strategic direction.

	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)
Today (1)	❍	❍	❍	❍	❍
Two years ago (2)	❍	❍	❍	❍	❍

ABOUT THE AUTHOR

Janene Culumber currently serves as the chief financial officer for Florida Orthopaedic Institute and for Florida Orthopaedic Institute Surgery Center. She also serves as a Supervisory Committee Member of the USF Federal Credit Union. Culumber previously served as senior vice president and chief financial officer for Moffitt Cancer Center. Prior to joining Moffitt, Culumber was a senior manager in the audit practice of KPMG LLP. She is a graduate of the University of Florida, where she earned a Master's of Accountancy and a Bachelor's of Science in Accounting.