BIG DATA CHALLENGES: ENHANCING STRATEGIC & OPERATIONAL DECISION MAKING FOR BUSINESSES

by Donald Lee

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A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Management

California University FCE via

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Abstract

Since 2005, Big Data analytics have been gaining traction and recognition as an essential and rewarding business resource to enhance strategic and operational decision making for business leaders. Big Data analytics consist of the 4 V’s of unstructured data—volume, velocity, variety, and veracity—stemming from nonstop 24/7 exchanges of emails, photo-sharing, and other Internet activities around the world. Big Data’s power lies in making targeted predictive analysis from mining messy, unstructured data points with machine learning, an aspect of artificial intelligence. Big Data analytics has upended the traditional use of data analysis for business intelligence to benefit businesses.

This research study employed the Interpretative Phenomenological Analysis (IPA) method to discern the lived experiences of data practitioners, executive-level decision makers located in the U.S. Pacific Northwest. Participant responses were unequivocal about Big Data analytics playing important roles for successful businesses to gain even more traction to achieve and maintain the competitive edge. Yet, as one respondent pointed out, the old carpenter saw of “Measure twice, cut one” still prevailed in being smart about analyzing an organizations’ business goals first—before deploying Big Data analytics. The findings suggested strong leadership was essential to articulate and motivate buy-in from all decision makers to achieve a collaborative approach to Big Data analytics for successful implementation. The implications for industry applications range from mining data points for healthcare and education to writing bestselling books.

*Keywords: Big Data analytics, business decision making, artificial intelligence, machine learning, predictive analysis*

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APPROVED BY DISSERTATION COMMITTEE:

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Dedication

This proposal is dedicated to my mother, Bettye Lee, who taught me the value of education and who has always encouraged me to do my best in life. To my dad, Donald Lee Sr. who encouraged me to keep learning, and to my sister, Andrea Ward, my daughters, and my sons who inspired me to be a role model that they can be proud of.

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# Chapter 1: Introduction

The focus of this research study is Big Data; more specifically, the implications of Big Data’s impact on today’s business environment and decision makers. The term Big Data is simply acknowledging the recent phenomenon of accumulating enormous amounts of data from myriad sources. To place Big Data within the current context, terabytes are increasingly replaced by petabytes and exabytes. If megabytes were a spoonful of sand, terabytes a sandbox two-feet wide and one-inch deep, then a petabyte stretches mile-long—with an exabyte stretching all along the coast from North Carolina up to Maine (Abbasi, Sarker, & Chiang, 2016). The term Big Data is also quite ambiguous because the roots of its definition are constantly changing, as do the diverse sources providing data for analysis (Provost & Fawcett, 2013; Wu, Buyya, & Ramamohanorao, 2016). Moreover, nearly all transactions, activities, and systems are increasingly leaving some form of data or traceability—information that people can potentially use for data analysis (Boyd & Crawford, 2012; Marr, 2015). However, the challenge of Big Data for businesses today is the creative ability to effectively integrate copious, never-ending cascading streams of data (business intelligence) into intelligible and effective business process management (Big Data analytics) for strategic and operational decision making (Davenport, 2014; Kopf & Homocianu, 2016).

The ultimate challenge and benefit in using Big Data lie in the utilitarian goal of extracting insights that smaller megabytes of data cannot reveal. This study will research how collecting and interpreting Big Data affect business organizations in their ability to manage the escalating growth of ever-changing, new data to help them maintain their competitive edge.

Therefore, the underlying premise and pattern of usage still hinges on human intelligence in making sense of exponentially compounding Big Data—and that is not all about technology, although artificial intelligence is important, too (Etzion & Aragon-Correa, 2016).

Big Data has also seen the growth of data analytics, which outpaced IT growth in 2011.

The U.S. Bureau of Labor Statistics in 2011 predicted a 24% increase for data scientists.

Furthermore, every dollar invested in Big Data resulted in $10.66 worth of value for chief information officers (CIOs) and chief financial officers (CFOs) as reported by Gartner, Inc., a leading IT research and advisory group (cited in Evans & Lindner, 2012).

Digital photographs, videos, telephone conversations, text messages, emails, GPS tracking data, exercise trackers, smartphones, social media data, websites, and the entire universe of the Internet are just a few common sources of data from which exabytes of information are accumulated. For example, businesses can use shopper zip codes and shopper smartphone locations to enhance visibility and affect highly targeted sales for products and services (McAfee & Brynjolfsson, 2012). Such common business data uses include consumer research and marketing, advertising, consumer behavior using predictive analysis, trade and commodities analysis, product sales and trending, logistic analysis and delivery route efficiencies, plus financial analysis (Flood, Jagadish, & Raschid, 2016; Krishna, 2015).

Businesses routinely carry out various data collection practices to inform and implement marketing and sales strategies. United Parcel Service (UPS) was one of the earliest companies to start tracking customers in 1954 (Marr, 2015). However, the growing types of data, the breakneck speeds at which data are continuously being generated, plus the sheer volume of data, are expanding at exponentially faster rates than most business organizations are capable of effectively managing, let alone analyzing, to more efficiently harness utilitarian benefits to impact the bottom line. The challenge to store large amounts of data has also driven organizations to be more selective about what types of data are most important to the organization. Simply buying more storage or using cloud storage solutions has become impractical or cost prohibitive (Marr, 2015).

The continuously exploding impact of Big Data exacerbates the four Vs: volume, velocity, variety, and veracity. The dynamic, ongoing flow of voluminous data necessitates storage capacities, and strains computational capabilities. The speed and velocity at which data pour in also strain bandwidth capacities. The sheer variety of data further poses problems of

integration when business information systems have not been designed to properly handle coordination, assembly, and integration. Given such massive volumes of data, error rates are heightened when they occur resulting in implications for veracity that also cause concern in potentially running streams of unverified data (Abbasi et al., 2016; Flood et al., 2016).

This study will also discuss the implications of Big Data’s accessibility to data sources considered as potential infringements on individual and organizational privacy. These ramifications affect socio-cultural, social, financial, political, and other norms of professional and personal conduct and boundaries. Finally, this study will introduce other opportunities to continue examining the ideas presented, and for research to fill in gaps towards expanding our understanding on how challenges presented by Big Data can become important decision- making tools for data scientists and business executives. As a relatively new phenomenon since unleashing the power of data analytics starting around 2005, Big Data is rapidly changing the business landscape—both in definition and in how targeted data can be leveraged to benefit businesses in maximizing cost efficiencies and production effectiveness (Efros & Torralba, 2016; Wu et al., 2016).

# Background of the Study

Successful business organizations have always used some form or type of data to plan, organize, and operate businesses to achieve the organization’s goals; thus the concept of business analytics. This underlying premise of using data for business gains remains true in the Information Age. However, leading edge technologies plus associated tools and techniques to implement technological advances continue to evolve and change significantly. They become outdated in as short a span as five years (Davenport, 2014). The data management, use, storage, analytics, and in deriving value from data for businesses is a common strategic and operational practice; as is evident with the traditional strategy of storing large amounts of data on disks.

However, Data Warehousing, data marts, and Extract Transfer & Load (ETL) systems and tools are getting to be familiar components of today’s business intelligence landscape. Yet,

changes in the numerous ways data are sourced and the rapid speeds at which data are being generated have prompted major changes in business intelligence and data analytics technologies. This sea change in technologies is rapidly transforming the way businesses operate in terms of gathering business intelligence and performing Big Data analytics for effective learning applications. The speed of information exchange (velocity), the amount of data being exchanged (volume), and the new, varying types of data (variety) have all contributed to a new era of data driven strategies to obtain a competitive advantage in business with powerful and swift technologies such as Hadoop (Trifu & Ivan, 2016).

Hadoop consists of free, open source software programs data scientists or anyone can adapt to analyze Big Data. Hadoop’s four main components comprise: (a) the Distributed File System stores data; (b) MapReduce maps out germane data and reduces data to comprehensible dimensions for the user to decipher data that have been extracted; (c) Hadoop Common in providing Java tools to read data with; and (d) Yarn, which manages resources for storing data and running analyses. Introduced in 2005 by Apache Software Foundation, Hadoop now has numerous associated programs that afford data scientists the flexibility of extracting and scaling data to reflect their ever-changing needs (Marr, 2015).

The overwhelming onslaught of Big Data has become more complicated and inexplicable—further challenging the limited human mind to make sense out of deciphering and interpreting continuous and copious realms of the unknown. In fact, data scientists see a paradigm shift in turning away from mining data to fit hypotheses and theories, to using data to build theoretical frameworks. Even more astounding is the observation that data scientists are now refocusing from a knowledge-based point of view to one that is ignorance-based in their efforts to make sense of unstructured, messy Big Data (Erevelles, Fukawa, & Swayne, 2015; Sammut & Sartawi, 2012).

# Problem Statement

Just as business intelligence and business analytics were important in defining business outcomes from 1987-2005, Big Data analytics is a term now commonly used to refer to the ability to analyze enormous volumes of data for targeted purposes. Today’s data experts are just beginning to scratch the surface in helping all major industries better understand data accumulations and how to appropriately address the challenges of Big Data. The newer, current strategies of Big Data analytics are capable of managing large volumes of data, the types of data collected, the challenges around privacy, security, legal discovery, governance, and compliance—to produce results that can ultimately become superior to human intelligence (Davenport, 2014).

Data scientists are beginning to develop and incorporate new tools and techniques beyond those widely known in the business intelligence industry to create new analytical models to address business usage in ways never before carried out. Data scientists are developing high-capacity computational neural networks facilitating artificial intelligence to pursue machine learning (Efros & Torralba, 2016). Machine learning facilitates incorporating copious amounts of data—from social media, smart phone data, health and wellness data, and even data generated from simple activities such as downloading music for simple enjoyment or reading an eBook—into neural networks that enable machine learning to produce outcomes besting humans.

For instance, Google’s AlphaGo was the first software program created to defeat world champion Lee Sedol (holder of 18 world titles for the past decade) in the classic game of Go which originated in China over 2,500 years ago. Over 200 million viewers witnessed the events in March 2016 to see Google AlphaGo defeat world champion Lee Sedol in 4-1 games.

Artificial intelligence is now able to overtake human intelligence—created by machine learning based on artificial neural networks (Koch, 2016; Silver, Huang, Maddison, Guez, Sifre, Van Den Driessche, ... & Dieleman, 2016).

The sheer volume, velocity, variety, and veracity of data have overwhelmed the business landscape; specifically, in challenging decision makers on how best to assemble, interpret, and integrate data to meet specific needs such as cost reductions and production efficiencies. Traditional methods of turning marketing data into business value with business analytics are quickly becoming technologically obsolete (Elliot, 2011). Instead, managing Big Data, conducting analytics, and ultimately turning data into business value in today’s rapid pace of data collection and voluminous data collections have spawned significant challenges in all aspects of data driven decision-making to enable businesses to perform beneficial predictive behavior using cutting-edge and constantly evolving algorithms (Arnus, Buxaderas, & Alvarez, 2015).

In essence, the current approach to business intelligence has moved on—from employing the concept of business analytics to more targeted focusing on enabling decision makers to make sense of Big Data analytics. The most cost-effective approach for Big Data analytics is to harness machine learning based on cloud computing efficiencies. Machine learning is the process of artificial intelligence drawing meaning from reams of data, with inferences drawn from data produced by algorithmic analyses which have been previously analyzed. In constantly honing and refining on previously mined data that also includes new data, the neural networks of machines have become self-learning from using deep learning algorithms, as in the example of AlphaGo defeating a Go master’s world champion (Koch, 2016; Wu et al., 2016).

# Purpose of the Study

To more properly reflect the purpose of this study, the research methodology will use a qualitative, interpretive phenomenological analysis (IPA) using an open-ended survey approach. This study seeks to explore how two business leaders, two IT managers, and two data scientists perceive the challenges of Big Data. Responses from these six participants will reveal their insights on how they analyze, use, and manage Big Data from unstructured data

gathered from social media, sensor data, and GPS data (as distinct from more traditionally structured data accessed from data warehouses). These findings are expected to fill in and expand knowledge gaps on how Big Data decision makers achieve optimal value from collecting and analyzing such large volumes of seemingly insignificant data to enhance strategic and operational decision-making. This study will examine how organizations are beginning to make the technological transformation from traditional methods of making strategic and operational decisions using business analytics to more advanced approaches of employing Big Data analytics. The study will also consider several challenges of using Big Data—including the management of large volumes of data, the types of data collected, challenges surrounding privacy, security, legal discovery, governance, and compliance. Finally, the study will present areas of opportunity concerning Big Data and expand on opportunities for further research.

# Research Questions

The inquiry into Big Data analytics shows a paucity of research in this emerging discipline (compared to traditional business analytics). Based on the problem and the purpose of this study, the general research question proposed is: How do business leaders, IT managers, and data scientists analyze, use, and manage Big Data primarily consisting of unstructured data gathered from social media, sensor data, and GPS data? (This overall question also presupposes Big Data users to incorporate some structured data accessed from traditional sources such as data warehouses.)

The following research sub-questions expand upon the general research question:

RQ1: How do business leaders, IT managers, and data scientists perceive Big Data (gathered from non-traditional and unstructured sources such as social media, sensor data, and GPS data) influence business and IT environments operations?

RQ2: How do business leaders, IT managers, and data scientists perceive Big Data (gathered from non-traditional and unstructured sources such as social media, sensor data, and

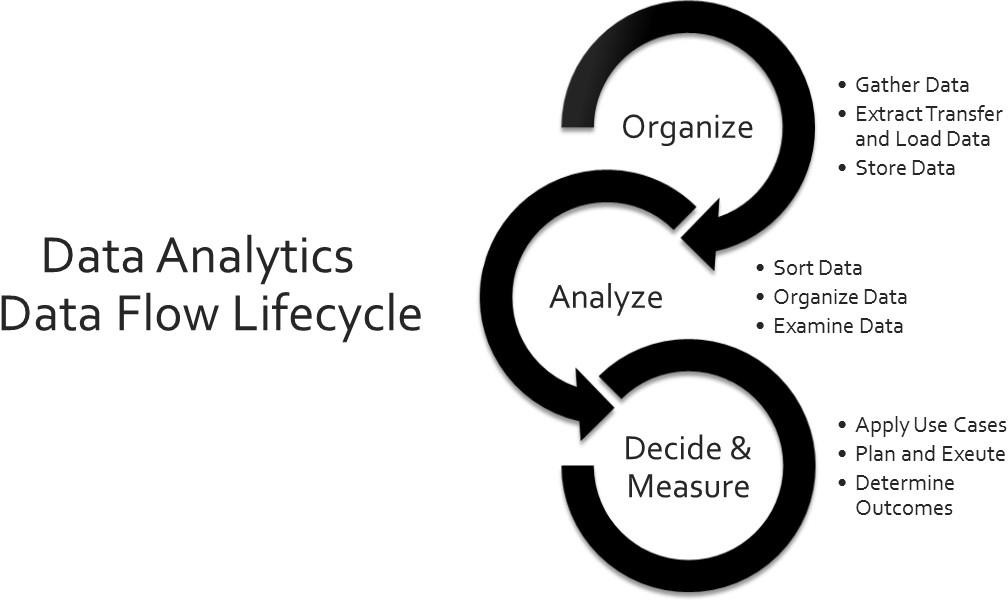
GPS data) as influencing strategic and operational decisions to gain and maintain the competitive advantage?

RQ3: What do business leaders, IT managers, and data scientists perceive are significant challenges that Big Data (gathered from non-traditional and unstructured sources such as social media, sensor data, and GPS data) have on strategic and operational decision- making?

# Conceptual Framework

The conceptual framework for this research study references a data analysis lifecycle that comprises a basic data analytics model. Organizations focus on gathering the key components of data organization from various sources and employ various techniques for data gathering. The process includes automated tools and techniques for data collection, extraction, transfer, and loading data into disparate systems. Organizations use a multitude of methodologies to analyze data. The process of analyzing data is called data analytics. More in- depth organization and categorization by data type and/or other common filters relative to the type of data being analyzed are then applied for further examination and analysis. At this stage, the data begins to become intelligible and useful to the business as potentially actionable information for decision-making (Marr, 2015).

The final key component of this process allows the organization the ability to make strategic and operational decisions for implementation to enhance production and marketing outcomes. This strategic process involving Big Data often results in a new, repurposed, or changed business entity or business model that more closely aligns to the organization’s plan in gaining and maintaining a competitive advantage over competition.



*Figure 1.* Data Flow Lifecycle for Data Analytics. Source:

Although new methods for organizing, analyzing, measuring, and ultimately making data-driven decisions have emerged for Big Data, an understanding of the methods, tools, and techniques required to properly execute Big Data analytics and data flow lifecycles is still evolving—including developing university courses on Big Data (Evans & Lindner, 2012).

Admittedly, many corporate CEOs have yet to hear of Big Data, understand what this concept means, and how Big Data affects their organizations. Furthermore, most organizations lack the talent, systems, and resources to implement a Big Data framework within their organizations. Apart from organizations such as Facebook, Amazon, and major retailers such as Wal-Mart specializing in data-driven decision-making, many organizations are just now beginning to understand what types of data they have; plus attempting to determine what they need to graduate beyond the first phase of the data analytics data flow lifecycle (Marr, 2015).

Thus, the appropriate business theory selected for analyzing results from this study is Peter Viall’s (1986) High Performance Systems (HPS) theory. HPS theory explains how high performing teams and organizations are more proficient in producing leading edge business

results for team efficiencies and productivity using smart strategic and operational decisions.

This seminal business theory continues to be widely used by new startups even today, to get up to speed with production outcomes (Viall, 1986).

# Nature of the Study

Big Data is an emerging concept and phenomenon (since 2005) that is constantly evolving to manage, analyze, and inform data-driven decision-making based on large volumes of unstructured data such as social media data, sensor data, GPS data, audio recordings, video, websites, PDFs, emails, and text messages (Marr, 2015). Big Data analytics is the very opposite of using traditionally structured data of names, addresses, zip codes, and point-of-sale (POS) transaction data to mine consumer information for strategic decision-making, as is the case for business analytics. Big Data encompasses both structured and unstructured data. More specifically, each organization needs to understand what their strategic and operational goals are, to effectively effectively implement the data analytics data flow lifecycle shown in Figure 1—to produce cost efficiencies and maintaining high quality production outcomes.

# Definitions

The study uses several technical terms listed below, which reflect Big Data’s unstructured data. These definitions are culled from an early and leading Big Data researcher, Bernard Marr (2015) and other emerging sources. To reiterate, because the new discipline of Big Data (which started gaining recognition only from 2005 on), is still shifting in terms of definitions and parameters, new emergent themes and processes continue to develop with unstructured Big Data analyses.

*Big Data:* This term describes an advanced form of data collection in managing, analyzing, and producing information that can inform and assist businesses and organizations in making cost-effective operational and strategic decisions.

*Big Data analytics:* Unlike traditional business analytics where structured data are used, Big Data analytics employs constantly shifting unstructured data to analyze unknown data for insights into predicting real-time trends, events, and consumer patterns.

*Business intelligence:* The process of gathering data from structured and unstructured data sources for business insights.

*Business process management (BPM):* The concept that recognizes how business and digital opportunities can be integrated to leverage and optimize organizational assets.

*Data analytics:* The process of accessing, integrating, and interpreting data to benefit an organization’s goals and targeted activities

*Data mart:* Smaller data organizations that sell specific data sets to organizations.

*Data warehouse:* Larger data organizations that sell specific data sets to organizations.

*Data scientist:* A data professional proficient in accessing and interpreting data from various disciplines—such as statistics, math, IT, psychosocial, consumer marketing, organizational management—in quickly developing functional predictive information from mainly unstructured (while also including structured) data.

*Extract transfer and load system (ETL):* Because Big Data is messy and unstructured, data have to be carefully extracted, transferred to storage according to variables, then loaded into databases by data warehouses; which also constantly update data.

*Global Positioning System (GPS):* GPS data sensors provide a wealth of data from

users.

*Hadoop:* A free, open source software program regarded as the backbone of Big Data analytics in enabling data scientists to adapt, scale, and build their own datasets.

*Machine learning:* Powerful algorithms enabling computers to learn from previously analyzed data in correctly predicting human behavior and outcomes.

*MapResource:* A Google open source software program used in Hadoop applications.

*Neural networks:* Powerful interconnected algorithms capable of inferring learning from previously analyzed information sourced from unstructured data, e.g. social media posts.

*Sensor data:* User movement and activity are collected by sensors to program outcomes; e.g., Google’s Nest for home and security applications (although Nest is now being folded into the emerging Google Home).

*Structured data:* Traditional forms of data sourced from surveys, point-of-sales, etc.

*Unstructured data:* Since 2005, Big Data from various tracking (GPS, sensor) and Internet (websites, social media texts, etc.) sources have added to databases with information churn in continuously streaming new, unknown, messy data recording the activities of users. In turn, raw data has reversed how data analytics have been traditionally used to developing unknown variables that more accurately inform decision-making.

# Assumptions

Findings from the study are based on assumptions that respondents have participated in giving honest responses as best they could, and that their responses have not been empirically verified. The lived experiences of Interpretive Phenomenological Analysis or IPA participants are recognized as subjective realities as described through the meanings attributed by these respondents in interpreting their own unique experiences (Callary, Rathwell, & Young, 2015). The researcher assumed the six IPA respondents were experienced Big Data professionals consisting of two business managers, two IT managers, and two data scientists.

# Scope and Delimitations

The scope of this study is primarily limited to the context of large business organizations. This would include, but not necessarily limited to, mega-organizations such as Google, Amazon, Facebook, and Walmart, which provide the most current and applicable case studies and examples of Big Data use in business.

The scope of this study does not include a wider examination of Big Data involving organizations outside of the business environment such as federal, state, and municipal governments, educational institutions, law enforcement agencies, military organizations, organized crime syndicates, domestic and foreign intelligence organizations, and foreign or

domestic terrorist organizations. The status also does not explore in detail the many individual uses of Big Data such as personal health and wellness, amateur and professional sports, personal entertainment, or other similar personal applications and use of unstructured Big Data.

# Limitations

The limitations of this study are primarily a lack of empirical research and the opportunity for biased opinions to influence the accuracy of the research presented within the study. Every opportunity was taken to carefully crosscheck each source of research presented in this study with other similar research sources in an effort to present consistent information throughout the study.

# Significance of the Study

The significance of this study highlights Big Data’s impact on today’s strategic and operational decision-making in enterprises. More specifically, from examining the Interpretive Phenomenological Analysis (IPA) and findings from two business managers, two IT managers, and two data scientists in how they perceive the challenges of Big Data to effectively integrate copious, never-ending cascading streams of data (business intelligence) into intelligible and effective business process management (Big Data analytics) for strategic and operational decision-making. Participant responses will offer insights and fill knowledge gaps on how Big Data influence and create positive social change—from harnessing the power of unstructured data into designing predictive models with powerful predictive capabilities as shown by Google’s AlphaGo software.

# Chapter 2: Literature Review

The purpose for this research study is to examine the impact and influence of Big Data and its perceived value for decision-making by businesses leaders. This research purpose reflects the problem that most business executives are unaware of the potential benefits of Big Data in optimizing decision-making. Thus, the biggest challenge is for businesses to recognize the value of utilizing Big Data to enhance productivity and cost efficiencies, from appropriately harnessing Big Data for strategic and operational decision- making. This paradigm shift redefines data analytics from using traditional databases structured upon Structured Query Language (SQL) offered by database systems such as Oracle, Microsoft Access, and IBM—to using Big Data analytics based on open-source adaptations that are more targeted in optimizing decision-making results (De Mauro, Greco, & Grimaldi, 2015; [Giannakis](http://www.emeraldinsight.com/author/Giannakis%2C%2BMihalis), & [Louis,](http://www.emeraldinsight.com/author/Louis%2C%2BMichalis) 2016; Kitchin & Lauriault, 2015; Kshetri, 2014).

The need and the skillful capability to assess Big Data’s overall impact and effective outcomes for decision-making are growing more significant every moment, even while considering future research opportunities that have never been more different, evident, and in need of integration into every aspect of the organization (Davenport, 2014; Hazen, Skipper, Boone, & Hill, 2016). The implications for chief executive officers (CEOs), chief information officers (CIOs), and chief financial officers (CFOs) to integrate Big Data analytics and digital technologies for analyzing consumer behavior patterns have far-reaching implications for all organizations, including those in the government, academic, and nonprofit sectors (Ali & Kidd, 2014). Furthermore, not only for organizations in the United States, but also Big Data’s global impact upon the majority of organizations, given the interconnectedness of supply chain inter-dependencies and other operational support services (Erevelles, Fukawa, & Swayne, 2015; Zhang, et al., 2016).

The biggest challenge facing businesses is the problem that most CEOs, CIOs, and CFOs are unaware of the major potential impact Big Data have upon their organizations’ strategic and operational decision-making approaches (Banks, 2016). Many executives are still operating under the constraints of using structured data for data analysis to guide strategic operations such as supply chain management, hiring employees, and developing marketing and sales strategies (Whyte, Stasis, & Lindkvist, 2016). While in fact, Big Data analytics involves tapping into vast exponentially cascades of never-ending raw, unstructured data that CIOs and CFOs would find advantageous for analyzing real-time results and thus, results-driven applications (Zhang et al., 2016).

The search strategy for the literature review used Google Scholar, EBSCOHost, ProQuest, and ScienceDirect/Elsevier databases. Search terms used included *Big Data*, *Big Data analytics*, *Big Data shifts*, *business data analytics*, *structured data*, *unstructured data*, *data scientists*, *cybersecurity*, *strategic decision making for businesses*, *operational decision making*, and *personal data*. Using these keywords in various combinations, relevant studies were reviewed and culled from database searches, and those deemed relevant to this study were included in the literature review.

Citation sources from 2012-2016 made up 100% of the references; there was hardly a paucity of research studies. Probably reflective of its meteoric rise as a new research discipline, Big Data is currently widely studied by academic, research, and government organizations.

However, two seminal theoretical sources are from earlier periods on Viall’s (1986, 1998) High Performance Systems (HPS) theory.

First, the theoretical framework for High Performance Systems theory is described, including an explanation of how HPS theory affects businesses with positive outcomes and as well, to consider the challenges involved. This is followed by a discussion on HPS and its relevance in providing guidelines towards a better understanding of how Big Data analytics can contribute towards enhancing strategic and operational strategies decision making by business

leaders. To place HPS in proper context within today’s digital economy, the implications of Big Data analytics will be examined, and HPS theory will be referenced in analyzing research findings with implications for further research.

After a brief historical overview, relevant studies will be organized into categories. The main categories will be: (a) structured and unstructured data, (b) the Internet of Things (IoT),

(c) Big Data neural networks and machine learning, (d) how Big Data enhances predictive analytics, (e) Big Data and business marketing, (f) Big Data and privacy concerns, (g) Big Data and cybersecurity, and (h) challenges in using Big Data.

The literature review concludes with a summary of where research gaps currently exist.

Research gaps provide the rationale and significance for this study to expand on knowledge that is vital to examine how the emerging phenomenon of Big Data analytics for businesses contributes towards enhancing social change. More specifically, how Big Data analytics affect, and may possibly enhance, the strategic and operational decision making of business leaders.

# Conceptual Framework

Peter Viall’s (1986; 1998) High Performance Systems (HPS) theory is an appropriate business theory to reference in guiding the development of the conceptual framework for this study, and in analyzing phenomenological findings from this study. HPS theory explains how high performance teams and organizations are more proficient and efficient in producing outstanding business results from team efficiencies and enhanced productivity fin using smart strategic and operational decisions envisioned by team leaders and members. Furthermore, successful HPS organizations endure challenges that outlast competition. This seminal business theory continues to be widely referenced by business startups even 30 years after its introduction, on how enterprises can get up to speed with high quality production outcomes (Viall, 1986). The need to endure in business is even more challenging for business leaders who have to make decisions that can enhance business outcomes from recognizing the benefits of Big Data analytics.

For example, Janz (2014) found highly motivated business teams working on a great product had the potential to self-destruct if a cohesive team spirit did not evolve to enable group members to work together constructively while adopting new ideas. Or, people simply ignored improving group effectiveness that would have come from adopting innovations facilitating high performance activities and therefore, quality outcomes that boosted overall productivity and team morale. HPS theory thus makes the case for studying how adopting Big Data analytics is an innovative step that could possibly enhance strategic and operational decisions for decision-makers and team members, to result in improving overall organizational effectiveness.

Janz (2014) adapted Viall’s HPS theory in studying technological startups. All the teams he studied were highly motivated business teams; he observed that High Performance Teams (HPTs) were those teams where members were highly satisfied with perceptions of their own personal performances and overall satisfaction as being a team member. Inevitably, these teams perceived a solid, common purpose that every member strived to achieve and maintain; were very collaborative with a common identity; possessed complementary skills among team members; and exhibited a high sense of autonomy with team members rotating as leaders.

Such collaborative team-building strengths resulted in superior outcomes, noted Janz (2014). In defining Big Data scientists, the U.S. Bureau of Labor Statistics (2016) expressed similar requirements. Big Data scientists need to possess cross-disciplinary adaptability and collaborative skills in addition to being productive team members solidly working together on one big project with a common goal.

This is the rationale for selecting Viall’s (1986) HPS theory for this study’s conceptual framework. HPS theory will also guide the analysis of research findings to explain how decision makers who adopt Big Data enhance strategic and operational outcomes for

their businesses. Furthermore, Janz’ (2014) research has found HPS theory explains why successful technological startups are enduring, and not others.

# Review of the Relevant Literature

Big Data analytics yield timely results and insights for tapping into consumer behavioral trends, in predicting and managing unforeseen changes for inventory controls, for production efficiencies, and in supply chain responses to cost reductions. All these operational arms of a business act together, and are especially critical to coordinate when responding to unforeseen obstacles and threats. Unpredictable business contingencies are inevitable situational variables requiring immediate attention for every business, from large- scale operations such as military and airplane production to mid-sized enterprises and small businesses (Ali & Kidd, 2014).

However seemingly, and an almost implausible benefit in meeting and solving contingencies (but fast becoming a real-time boon for resolving business uncertainties as explained in Chapter 1), is the increasingly significant role of machine learning bestowed by Big Data networking computer algorithms. Machine learning affects the predictive capabilities of organizations to anticipate chaos while enhancing production—based upon the computer’s ability to continuously and repeatedly perform deep reinforcement learning techniques—from accurately predicting outcomes crunched from messy and imprecise data such as smartphone exchanges (emails, text messages, photo-sharing, etc.) and other forms of viral data exchanges. Machine learning is a repetitive learning method where computer neural networks of algorithms (similar to human neural networks wired for cognitive capabilities)

re-analyze previously analyzed data drawn from unstructured, raw, and messy data to generate accurate predictive capabilities that are getting more sophisticated in helping organizations advance against competition. This paradigm shift away from data analytics to Big Data analytics is a compelling scientific data revolution affecting every discipline (King, 2014; Koch, 2016; Winthrop & McGivney, 2016).

Therefore, the research question to explore is: Why are so many executive decision- makers unaware of, or are seemingly unprepared for, the critical need to switch from today’s business data analytics to harnessing Big Data analytics for cost-effective operational strategies and decision-making? What insights do data scientists and business managers suggest are timely issues for business leaders to consider? How can businesses transition as seamlessly as possible into harnessing Big Data analytics for effective strategic and operational decision-making?

# Historical Overview of Big Data

Businesses have traditionally employed structured data to streamline project production demands for inventory control, supply chain management, and product delivery— including other organizational activities such as projecting hiring or human resource needs and marketing new product launches. One reason for the continued use of structured data is because, it is much easier in terms of handling data subsets (which already comprise voluminous amounts of data) to facilitate business development strategies in projecting demand and supply based needs. Structured data have been broken down into smaller quantified subsets by data marts; such data are more manageable, having been previously categorized and developed into more recognizable and usable subsets by data warehouses before being sold to data marts, and resold to businesses (Davenport, 2014).

Other additional sources of structured data are from consumer devices with sensors such as global positioning system (GPS) tracking devices and network sensors embedded in electronic devices such as smartphones and appliances. Smaller data subsets from in-house collections gleaned from customer names, zip codes, and point-of-sale (or POS) for strategic and operational analyses are also employed in analyzing consumer data. As early as 1954, United Parcel Service (UPS) had started its own in-house analytics group (Davenport, 2014).

Early on in the New Millennium, the expression “Big Data” was believed to have been coined by scientists in the disciplines of astronomy and genomics; and has gained wider

acceptance and put to practical use. Since then, and noticeably beginning in 2005, a sea shift has occurred with the explosive arrival of Big Data analytics, and the arrival of a new profession—that of data scientists (Marr, 2015). In 2011, the movie *Moneyball* which starred actor Brad Pitt showed how a low-budget baseball team like the Oakland A’s mined accumulated data and baseball statistics to come up on top in signing on under-valued players (Perrons & Jensen, 2015). The amorphous designation of Big Data showed unparalleled promise for a new scientific paradigm shift, so much so that Harvard University’s Institute for Quantitative Social Science director King (2014) predicted no area would be left untouched by Big Data.

Data analysts engaged in analytics research observed how the commercial collection, accumulation, and integration of data for strategic business purposes was rapidly changing the course of data analytics because of the exponential increases and non-stop output in more voluminous, more varied data generated at higher velocities; hence the reference to Big Data analytics (Davenport, 2014; Ouellette, 2013). The never-ending, continuous flows of unstructured data was bolstered by the Internet’s 24/7 displays of information and communication output along with simultaneous sharing by users all around the globe. The Internet transcended time and place, and opened up vast possibilities in applying the power of Big Data analytics to shape even more compelling business development uses with real-time applications (McAfee & Brynjolfsson, 2012).

Newer, copious developments for Big Data are growing more exponentially from integrating structured data with unstructured data. Big Data consist of the Internet’s non-stop flows of messaging texts, videos and video-sharing, photo-sharing, social media, emails, and website communications. Recently, the emergence of tracking apps that record an individual’s activities from calendaring events to measuring fitness rates are also adding to the mega-accumulations of Big Data (U.S. Bureau of Labor Statistics, 2013).

Provost and Fawcett (2013) indicated that it serves decision makers well to first, understand the concept of Big Data and how this phenomenon works in relation to other important aspects of running their organizations. Then second, to apply that newly acquired knowledge and understanding that is unique to each organization in identifying how Big Data components are related to, and are useful for, in repurposing the needs of their organization. While academic debates help uncover, measure, and discuss Big Data’s omnipresent activities in bringing awareness to business leaders, both authors indicated a targeted approach to using Big Data. It is only from analyzing Big Data in real world business applications within their own organizations that a better understanding can be arrived at by decision makers, as to how best to utilize Big Data for facilitating each organization’s unique strategic and operational decision making activities (Provost, & Fawcett, 2013).

# Structured and Unstructured Data

The “four Vs” of Big Data metrics are volume, velocity, variety, and veracity; which also overlap and necessitate capitalizing on traditional structured data for making informed decisions (Lagoze, 2014; Whyte et al., 2016). The runaway rate of new Big Data changing the business landscape with dynamic and unpredictable turns of events upon data analysis has necessitated developing new approaches in working with Big Data analytics (Marr, 2015).

However, many executive-level decision-makers are still unable, unaware, or unprepared to consider making the switch to apply Big Data analytics to better position their companies in the new digital economy (Flood et al., 2016; Krishna, 2015). Thus, the purpose of this study is to contribute with findings towards filling in knowledge gaps on how business leaders can optimize Big Data for strategic and operational decision-making.

On one level of change, the traditional reliance on structured data to produce reports purporting to understand variables such as consumer behavior, cost efficiencies, human resource allocations and other resources such as supply chain management is being challenged by the newer, never-ending onslaught of Big Data. Unlike structured data,

unstructured Big Data are imprecise and messy, thus difficult to categorize and quantify numerically; for instance, in categorizing exabytes of email messages and photo-sharing exchanges. Another level of challenge continues to affect the mindsets of the majority of CEOs, CFOs, and CIOs who are unprepared and untrained to recognize the exceptional value and implications of Big Data analytics to apply this vast treasure trove of raw data to enhance their organizational operations (Abbasi et al., 2016; Davenport, 2014; Marr, 2015). Therefore, a paradigm shift in the psychosocial awareness and acceptance by executive-level personnel is vital in accepting and using Big Data analytics, to more properly harness the powerful efficiencies of unstructured data with unknown variables—yet are paradoxically capable of producing powerful predictive effectiveness (Provost & Fawcett, 2013).

This new arena and growing awareness of the inherent value of utilizing Big Data is shaping the direction for a newly emerging vital profession—that of data scientists, of which there is a shortage, according to the U.S. Bureau of Labor Statistics (2013). Data scientists make sense out of, and manage, Big Data. Data scientists need to be open to creative problem-solving innovations. They are adept, and proficient across multi-disciplines such as statistics, applied mathematics, information technology (IT), coding for software development, and even schooled in psychosocial observations to analyze consumer behavior

related to Big Data production, to more accurately research and apply the powerful metrics of Big Data (Lagoze, 2014). An important personal skill set for data scientists is the ability to become creative problem-solvers who possess an intellectual curiosity with the ability to learn new things quickly. It is also vital for data scientists to collaborate well with others working on their teams because analyzing Big Data requires the coordinated skills of many individuals working on one project. Including the ability to communicate clearly to translate technical information for those with non-technical backgrounds; e.g., in working with graphic designers to accurately depict and illustrate Big Data concepts for easy comprehension, according to the U.S. Bureau of Labor Statistics (2013). Three years later, the *Wall Street*

*Journal* reported the Bureau of Labor Statistics will update job titles in 2018 to reflect the country’s high demand for data scientists and project managers to meet the rapid pace of technological advances and occupations that are increasing to fill these new positions (Weber, 2016).

In essence, Big Data has disrupted the historical notion of analyzing mega structured data—and forced decision makers running businesses to rethink their traditional approaches of using only business analytics. CEOs, CIOs, and CFOs are now having to think about out- of-the box, unique ways in relating voluminous amounts of unstructured data in trying to make sense out of non-traditional disruptions posed by Big Data, that more accurately reflect real-world and real-time activities with Big Data analytics and practical applications (Hazen et al., 2016). Such a paradigm shift in research approaches to consider Big Data’s challenges on strategic and operational operations necessitates behavioral changes in education and the modification of CEO, CIO, and CFO mindsets (Winthrop & McGivney, 2016).

Thus, the inherent problem facing many organizations in all sectors of the global economy—not only for business corporations, but also cutting across government agencies, higher education and academia, and the nonprofit sectors—is the challenge of learning new ways of integrating raw, unstructured data in shaping an organization’s goal-setting agenda. The critical immediate need is for data scientists to move away from solely analyzing traditional structured data towards skillfully combining structured data and Big Data to result in more informed real-world and real-time applications. For example, Aviva, a large insurance company based in England has developed algorithms to analyze consumer credit reports and marketing data, resulting in high probability analyses that are capable of identifying the health risks of potential insurance applicants. The added value of Big Data comes from not only monitoring customer relationships, but also in finding patterns from unknown variables that end up in accurately predicting consequences (Perrons & Jensen, 2015).

# The Internet of Things (IoT)

Related, and at the same time contributing, to the meteoric rise of unstructured and raw Big Data is the accompanying phenomenon of another digital frontier—the *Internet of Things* (IoT). The IoT is also called the Fourth Industrial Revolution and not without security concerns given the massive amounts of devices capable of exchanging private and confidential data (He, et al., 2016). The IoT comprises massive digital neural networks of raw data connecting people, things or devices, and processes (Breur, 2015; Harbor Research, 2016). Estimates are given that by 2020, there will be 75 billion devices connected to the Internet of Things (Riggins & Wamba, 2015).

The IoT uses reliable digital smart systems capitalizing on tracking data emitted by electronic sensors that seamlessly connect people and processes—to result in better decision making for individuals, businesses, and policy-makers. For instance, a patient while waiting for an appointment at the doctor’s office can email an order to a bakery on her smartphone, confirm her email was received, and to continue on her way to pick up a birthday cake after leaving her medical appointment. Then, upon driving to the bakery, she would hunt for a parking spot without losing time by using her smartphone’s auto parking sensor. Such a scenario is already happening and a boon to mitigating problems of traffic flow for people and places. For example, the City of San Francisco’s Municipal Transportation Agency in California reported 20%-30% of traffic congestions was caused by people trying to locate parking spaces—but smart systems picking up sensor tracking systems can ameliorate such problems to connect people with parking places, thanks to the IoT (Harbor Research, 2016).

In another example, homeowners today routinely prevail upon smart sensor systems to monitor and save money on their energy bills. This process effortlessly tracks residents’ energy usage based on their lighting and heating needs and patterns of use—while also contributing to the flow of unstructured data. However, on a more profound level of usage in terms of volume, variety, and velocity gleaned from Big Data analytics machine learning,

Google has developed “DeepMind” algorithms that go even further. From analyzing and reanalyzing previously analyzed data, Google’s “DeepMind” algorithms have helped produce more energy-efficient data center servers by significantly reducing energy consumption needed to cool these data center servers by 40 percent, and in the process also reduced by 15 percent the overall power use (Rich & Gao, 2016).

# Big Data Neural Networks and Machine Learning

The ever-advancing available avalanches of unstructured raw data are paradoxically turning around humongous amounts of exabytes of unknown variables into predictive and positive outcomes that help people navigate and make sense of the unknown, plus help businesses profit from making better decisions. For example, based on harnessing smart systems capable of analyzing Big Data in the case of Google’s DeepMind artificial intelligence technologies, smart systems of machine learning enhancements use smart algorithms to learn from repetitively analyzing previous analyses to produce cost-savings results with energy use as reported in the previous paragraph (Rich & Gao, 2016). The applications for neural network algorithms are myriad.

In the case of Google’s AlphaGo, Google’s DeepMind algorithms were able to produce self-learning software based on machine learning—even in competitive situations. Machine learning prevails upon the concept of “deep reinforcement learning.” For instance, AlphaGo roundly trounced a decade-long world master champion in the complex 2,500-year old Chinese game of Go (Koch, 2016; Silver et al., 2016).

Moreover, advances in machine learning prevailing upon Big Data’s accurate predictive learning capabilities are not solely reserved for genius goliaths such as Google algorithms. Seventeen year-old Brittany Wenger’s interest in Big Data neural networks and computer programming yielded similar, efficacious results. Wenger was the 2012 Grand Prize Winner of the Google Science Fair. Wenger said she completely failed the first two times she

tried writing her breast cancer biopsy detection software—but persevered because this was the nature of science in being able to learn from failures (Borel, 2013).

Wenger first self-taught herself how to code software, then developed a program that predicted with 99 percent accuracy cancerous cells in breast tissue biopsies—based on machine learning. After school and during her spare time, Wenger’s goal was to figure out how her cousin’s breast cancer diagnosis could be improved earlier than later, to help numerous others (including men who do succumb to breast cancer although in smaller numbers). This teenager developed an artificial neural network that mimicked the brain’s neural network to develop a highly successful diagnostic program based on 7.6 million trials. The process of machine learning was capable of learning from, and tracking, vast volumes of data points to learn and detect patterns that the human eye could not—that could reveal discrepancies in biopsy tissue that had been hitherto invisible—with an unerring 99 percent accuracy (Marr, 2015).

What do these real-life successful stories and lessons in applying Big Data offer for business (plus others, including academic and government) decision-makers, and individuals have in common? If a concerned individual such as a 17 year-old can successfully take on the challenges of working with Big Data, in what ways, and how can business leaders apply Big Data’s challenges to strategic and operational decisions to enhance business outcomes? The goal and the answer are simple in every case—to problem solve challenging situations, with the goal of achieving enhanced decision-making, resulting in valuable outcomes and successful solutions for businesses and individuals (Regalado & Watts, 2014).

# Big Data Enhance Predictive Outcomes

In Australia, many retail merchants are well aware of the benefits in working with Big Data to improve the bottom line. In a 2015 survey conducted by Microsoft and Telsyte with over 300 organizations, almost half of Australian merchants indicated they would utilize the Internet of Things (IoT) within the next two years (Inside Retail, 2015). These Australian

retailers gave three reasons for deploying Big Data: (a) cost savings, (b) increasing revenues, and (c) productivity benefits. Furthermore, 28 percent of organizations experienced cost reductions in their daily operations. Additionally, 40 percent of those surveyed said the IoT (a trajectory of Big Data) will improve decision making for their businesses.

To reiterate, the limited capacities of data analytics using structured data with analyses carried out on limited platforms limit analyses for predictive implementation (which enhance business efficacies). Using structured data is unlike harnessing the mega, never-ending capacities of Big Data analytics to store, analyze, and integrate vast amounts of raw, unstructured, imprecise, and complex data for real-time analyses—to better benefit businesses, e.g., in targeting efficient supply chain management as opposed to keeping and monitoring inventory in stock. In 2000, 25 percent of stored data were digital. In 2015, 98 percent of stored data, mainly Big Data, went digital (Xu, Frankwick, & Ramirez, 2016).

For example, Netflix has successfully launched into producing in-house movies from analyzing vast data points captured from viewers, based on Big Data analytics. The strategy straddles real-time data collection; then plumbed for insights for viewer preferences on whether pilots would become successful movies feasible for Netflix to invest in. Data points were collected from unsuspecting viewers who cast their viewing preferences from using an invisible viewer voting system. Favorable ratings logically indicated to Netflix the business rationale to produce shows that viewers would be inclined to buy, thereby impacting the bottom line (Xu et al., 2016).

In the global fashion industry where fierce competition rules in setting seasonal fashion trends set by fashion houses with two annual seasonal showings in the Fall/Winter and Spring/Summer collections, Big Data is also casting an unseen, powerful impact. For instance, Big Data has upended the traditional business model based upon showing two annual fashion collections that fashion houses typically present. Instead, Big Data continues

to bolster the fortunes of Spanish fashion house Zara which has placed CEO Armancio Ortega as the world’s second richest person, after Bill Gates (Vinton, 2016).

While America is just waking up to how mega corporations such as Microsoft, Amazon, Facebook, and WalMart have been leveraging Big Data to dominate in their respective fields, Spanish fashion house Zara has been quietly using Big Data to emerge as a global fashion leader with mega-sized profitability in the billions. Zara emulates the velocity and speed of Big Data by analyzing consumer fashion preferences—to produce at least four annual fashion collections each year. Furthermore, instead of having to dispose of unsold inventory, clothing styles that did not excite customers are discontinued, which also frees up storage and the need for stock and inventory control. This Big Data analytics strategy makes room for fast-forward business innovations that more accurately meet and target customer preferences, instead of a fashion house dictating to customers what may possibly sell based on traditional data analytics. Currently, other high-end, cached, and respected European fashion houses such as the French Louis Vuitton and the Italian Prada style leaders are also emulating the Spanish Zara business model in presenting four to six fashion collections every year—based on using Big Data analytics to better target consumers while hitting up profits (Roubelat, Brassett, McAllum, Hoffmann, & Kera, 2015).

Although Zara’s high fashion designs are dominant in capturing the consumer market, it is however not a high-end fashion house like Louis Vuitton and Prada. Rather, Zara is a savvy, high street, mass market fashion operation similar to Sweden’s H&M, Japan’s Uniqlo, and England’s Topshop. All these fashion marketers are adept in using Big Data in swiftly responding to fickle consumer tastes that change constantly. These fashion corporations react and capitalize on velocity and variety to meet voluminous consumer demands—not unlike Seattle’s Amazon.com, the world’s largest online retailer—while earning huge profits in smartly deploying Big Data for strategic and operational outcomes (Gordon & Perrey, 2015).

With the help of Big Data, Amazon is a historic textbook study in nimbly responding to constantly changing market demands—from anticipating and predicting customer demands based on cascading reams of consumer data. Amazon is skilled in crafting and recrafting voluminous supply chain management and marketing strategies in ably managing and coordinating faster restocking needs, to better satisfy consumers with one-day deliveries. For example, Amazon Prime’s same-day delivery services in some cities are unparalleled (Gordon & Perrey, 2015).

# Big Data Enhance Business Marketing

Along with the mechanics and logistics of seamlessly executing same-day deliveries, Amazon’s vast online store shopping experiences are further fueled by loyal customers who shout out their approval (or disapproval) with sharing them on social media networks. In this era of social media sharing, customers are able to share their immediate responses and experiences instantaneously. Social media exchanges are all parts of unstructured, raw nuggets of Big Data that are continuously being mined to discover trends and consumer behavior for Big Data analytics—with the goal of optimizing business profits (Roubelat et al., 2015).

Rather than fearing negative feedback, Amazon has the business savvy to parlay such comments into positive outcomes with almost immediate damage control (instead of allowing unattended complaints to fester) by being responsive with apologies, “no-questions asked returns,” and incentives to further deepen customer loyalty. In the process of satisfied customers sharing their experiences, Amazon just keeps on extending its ever-growing vast networks of social media influencers and consumers (Gordon & Perrey, 2015).

Big Data has taken yet another futuristic turn on consumer marketing in deploying simplicity, speed, and storytelling for businesses to churn the wheels of traditional commerce into bigger, faster profits. Customer feedback has also morphed into customers co-developing and suggesting user-friendly functionalities to enhance the online retail experience. Another

similar digital shopping example is the German carmaker Diamler’s “Mercedes Me” brand marketing catering to individual preferences, where customers are welcomed to express preferences for custom-ordered cars specifically designed to cater to their tastes (Gordon & Perrey, 2015).

The era of Big Data decision making for operations control and lucrative strategic enhancements continue to enrich business owners. However, enhanced outcomes are only possible if decision-makers know their businesses inside out and understand what needs to be enhanced from using Big Data analytics. These are primarily business leaders who have the vision to adapt and to custom-develop strategic marketing tactics using Big Data to serve their business clientele while working seamlessly with online developers and data scientists to enhance user-friendly functionalities and customer experiences (Wang, Gunasekaran, Ngai, & Papadopoulos, 2016).

Consumer ratings and user reviews posted online are fast becoming the norm in predicting consumer purchases and patterns of usage. Not only for smaller consumer items such as fashion, but also for larger homeownership products, Big Data are leading the way in using unstructured data based on consumer transparency. For example, unstructured data form the basis for insights as to why consumers would buy renewable, organic biomass (wood, animal waste, seaweed, etc.) materials for heating purposes. One company used the marketing strategy of gathering user ratings and reviews (unstructured data) that were then analyzed in terms of consumer discussion points. This was followed up by mapping out behavioral sequences of how homeowners made their final purchases (Athiyaman, 2015). The simplicity of Internet transparency generated by online user discussions, storytelling, and reviews is speeding up the marketing process for businesses today. Instead of fearing unstructured feedback, smart marketing decision makers are encouraging consumers to generate favorable feedback while turning around negative reviews into positive experiences (Gordon & Perrey, 2015).

Whether consumers shop for brick-and-mortar store or online purchases, they expect ease and engaging personalization with their shopping experiences. Consumer shopping ranges the spectrum, from quality products, to travel-related services and professional services. Using simple marketing insights gleaned from Big Data will produce payoffs for businesses—even as these interactions add to the ongoing accumulation of Big Data (Weber & Prodromou, 2015).

For instance, the rapidly growing hospitality Airbnb industry contributes exabytes of host and rental nuggets of information which are continuously mined for ever-expanding marketing insights. Prospective travel-renters start by opening user accounts on Airbnb’s website through their Facebook or Google+ accounts, or using valid emails. They post their profile information in their Airbnb accounts. This step verifies their identities by linking their social media profiles to their Airbnb accounts. Meanwhile, the process keeps on adding more unstructured information for Big Data.

Airbnb’s data science leader, Elena Grewal, called Big Data analytics a powerful lens in helping create social change and the acceptance of new ideas. Airbnb is a cutting-edge hospitality innovation valued as a $25.5 billion unicorn startup. (A unicorn is Silicon Valley’s term for startups with the potential to grow exponentially and hence start out operating with the advantageous edge of being valued at $1 billion and beyond.) When Grewal started in 2012, Airbnb had five data scientists; four years later, she leads a team of over 50 data scientists. Grewal took the initiative to learn software coding skills to develop customized programs; her coding skills are further parlayed into proprietary software for organizing Big Data that continue to pour into Airbnb’s databases. Grewal called data scientists “interpreters” who distilled the voices and opinions of Airbnb customers “to help inform our products” (Lien, 2016).

The customer-centric business model facilitated by the Internet’s 24/7 easy access and convenience is a growing marketing strategy gaining fast traction, where business owners

also capitalize on increasing brand awareness with prospects (through word-of-mouth advertising and web surfing) and repeat customers. Superior online marketing and shopping experiences reward both businesses and customers when websites are: (a) user-friendly, (b) well-designed with engaging and informative content, (c) conscious of offering high quality and unique items, and (d) supportive and interactive with human interactions facilitating a variety of contact choices such as phone number, email, and chat boards (Weber & Prodromou, 2015). As the innovative Big Data applications of Airbnb, Netflix, Zara, and Google’s DeepMind show, mining customer data is more cost-effective and accurate than holding expensive focus groups (Athiyaman, 2015; Wang et al., 2016).

Big Data analytics are also assisting accounting professionals analyze and audit financial reports with predictive accuracy. In auditing financial reports, analyzing Big Data assists with inspecting, cleaning up, interpreting, and modeling information along the audit trail. These audit trails uncover valuable patterns of information, and suggest useful conclusions for decision-making (Cao, Chychyla, & Stewart, 2015).

As Marr (2015) reported, even a high school teenager like Brittany Wenger can hack Big Data points to create a software program that analyzes biopsy reports with 99 percent accuracy. Moreover, as Microsoft’s study in Australia showed, smaller and mid-sized retailers can learn from the “big guys.” The strategy is simple; but the processes involved entail detailed analyses along with the patience to keep on analyzing and reanalyzing previously analyzed data points to distill core insights. The research goal of Big Data analytics is to understand how companies fill the unmet needs of customers and how to mitigate consumer pain points. The logical next step results in applying these insights to custom-design Big Data analytics unique to the enterprise’ strategic and operational goals, to support inventory control, supply chain management, targeted marketing strategies to satisfy customer needs, and in fulfilling human resource needs (Inside Retail, 2015).

Similar concerns of not using data smartly are prevalent in other diverse industries such as the oil and gas industry—where Big Data has the potential to reshape the entire industry (Perrons & Jensen, 2015). The oil and gas industry acquires vast amounts of information it mines with massive datasets utilized for descriptive purposes. However, much of the useful data are either discarded, or ignored.

With so much discussion of personal preferences and the disclosure of personal data and viewpoints, should consumers be concerned about privacy issues? Most consumers are indeed concerned and many are aware of the need to curtail sharing, especially in personal areas such as healthcare and financial data. As in any endeavor, opportunities for misuse arise and cybersecurity is a major problem (Campos, Sharma, Jantunen, Baglee, & Fumagalli, 2016).

# Big Data and Privacy Concerns

When the U.S. Congress passed Public Law 104-191 in 1996, the Health Insurance Portability and Accountability Act (HIPAA) guaranteed patient privacy for patient information shared with traditional healthcare organizations such as insurance providers, hospitals, and medical practitioners, among other health providers. However, given the incredible velocity, variety, and volume of personal health and wellness apps spawned by today’s digital technologies, patient data are no longer confidential outside of HIPAA agencies. That is, anyone who wears apps and devices prescribed by their doctors to monitor health and safety concerns are still protected by HIPAA’s privacy laws. However, anyone who discusses their health concerns with online discussion groups and wears non-medically prescribed fitness tracking devices will open up their personal histories with no guarantee of protection from privacy issues (U.S. Department of Health and Human Services, 2016).

In the short of span of just two decades, speeds at which technological advances have progressed have thrown a loss of privacy curve to app users sporting, health, and fitness devices issued by tech companies. These seemingly innocuous bits of personal demographics,

medical, and health information that are digitally tracked snowball into torrential exabytes of Big Data that can be accessed by anyone and any organization. Most app programs are unencrypted, and thus cause for concern that private information can be easily intercepted by any individual or organization. A person’s online location, their medical search terms and keywords entered into browsers, and browser habits reveal private nuggets to hackers— silently and often unbeknownst to the individual, until it is too late (Banks, 2016; Mansfield- Devine, 2016).

For example, Target’s Big Data analytics team was so accurate with predictive analyses in sending out pregnancy-related coupons to entice pregnant mothers that they stumbled upon an irate father who questioned whether Target was trying to get his teenaged daughter to become pregnant. As it turned out, the father had to apologize to Target instead. He had been unaware of his daughter’s pregnancy; this incident occurred in 2012 (Chen, 2016).

Predictive analysis using Big Data routinely shows how accurate analyses can get— and how it can enhance marketing and in achieving sales goals for businesses. It is not hard for Big Data to pinpoint a person’s medical condition; thus, it works both ways. Big Data is handy in monitoring and alerting medical personnel about a patient’s health and safety issues, and online discussion can help people share information on diagnoses and relevant sources for patient healthcare support and wellness assistance. However, Big Data can also throw a curve in making public very private user information not covered by HIPAA. Data recorded on lifestyle, calendar, exercise, home heating apps and other sensor tracking apps—including online browser information tracked by cookies, as the Target teen pregnancy story illustrates—are gold mines of consumer information just waiting for businesses to adroitly explore, mine, and profit from. Meanwhile, potential dangers abound for those who are unsuspecting in downloading “free” apps with tradeoffs in sacrificing nuggets of personal identification (Chen, 2016; Heires, 2016).

Contrary to disclaimers on websites that tracking cookies enhance visitor experiences, they can also reveal information that could be unintended for public forums and social media sites; e.g., an individual’s irregular sleep habits or food allergies. According to the U.S. Department of Health and Human Services (2016), 27 percent of Internet users and 20 percent of adults have their personal demographics tracked online which offer up information details such as weight, diet, and chronic health symptoms. Apart from wearable sensors such as the Fitbit exercise sensor tracker, Big Data analytics also obtain information from smartphones, tablets, and other software uses. The only recourse for consumers is the Federal Trade Commission (FTC) protection ruling; if non-HIPAA vendors are caught using individual data in deceptive and unfair ways, vendors are liable for prosecution by the federal government (U.S. Department of Health and Human Services, 2016).

# Big Data and Cybersecurity

The threat of cybersecurity and its impact on Big Data is a major concern, as voiced by numerous researchers (Campos et al., 2016; Flood et al., 2016; Las-Casas, Dias, Meira, & Guedes, 2016; Sutikno, Stiawan, & Subroto, 2014; Thuraisingham, 2015) and government agencies such as the National Aeronautics and Space Agency or NASA (Hinke & Shaw, 2015). For example, in 2015 the costs of cyberattacks resulting from data breaches cost an average of $4 million per incidence—up from $3.8 million in 2014. Additionally, this global study of 2015 Big Data by the Ponemon Institute projected the likelihood of data breaches consisting of at least 10,000 stolen records per incident at 26 percent, would take place in the following 24 months. This worldwide study involved 12 countries (Ponemon Institute, 2016).

In 2011, the White House’s strategic cybersecurity plan called for developing cybersecurity research to recognize the need to move away from conceptualizing security as an engineering plan to an effort that resembles a scientific endeavor. The reason given was engineering approaches are mainly reactive and thus ad hoc in responding to cyberattacks.

Instead, developing a scientifically proven and preemptive approach would be more useful for all purposes and industries (Graves, Acquisti, & Christin, 2016).

Since 2011, research and national funding agencies have responded to the White House plan by viewing Big Data as a valuable scientific research endeavor. A science of cybersecurity according to this White House plan would encompass: (a) security laws, (b) “first principles” transcending specific technologies and systems, (c) the ability to create models and abstractions that can undergo rigorous experimentation, replication, and treatments, and (d) resulting in the ability to generate generalizable results. The goal is for a truly defensible cyber system in the event of attacks, plus also anticipating attacks (Graves et al., 2016).

Flood et al. (2016) pointed out there are privacy and security issues concerning “linkage attacks” stemming from the interconnectedness of unstructured data and multi-layers of data that cannot be authenticated. Another instance is where a high-level federal agency such as NASA is constantly bombarded with spear phishing scams. Spear phishing is a targeted malware attack where the email sender purports to be an authentic manager or team leader and instructs the receiver to reveal confidential information. When an unsuspecting employee responds with the requested confidential details or clicks on the link provided in the email, top-level secrets would be siphoned off, if not caught in time. Malware is released in the process thus infecting not only the email receiver’s computer but also inevitably, the entire internal system of NASA or the organization (Hinke & Shaw, 2015; Las-Casas et al., 2016).

Even using a complex “Random Forest” algorithm and a three-layered approach, security detection rates for primarily unencrypted Internet of Things (IoT) exchanges were secure only 93.9% of the time—thus leaving over 6% of exchanges vulnerable to attacks (Khorshed, et al., 2015). However, the paradox of working with imprecise, messy, and unstructured raw data meant that Big Data analytics could also be recast as predictive analysis

tools to preempt cyberattacks by identifying potential security threats and risks in developing proactive counter measures to averting potential cyberattacks (Agrawal et al., 2012; Chen, Kazman, Monarch, & Wang, 2016; Tisdale, 2016).

The increasing use of mobile devices such as smartphones and tablets, plus sensor- location tracking devices for GPS, medical monitoring, smart home heating controls (e.g., Google’s Nest for thermostat adjustments) and appliance settings, including other purposes benefitting today’s lifestyle conveniences are all also cause for concern involving Big Data cybersecurity (Algarni & Malaiya, 2016). Personal information entered into mobile devices are among the most easily obtained by advertisers; yet, the majority of information flows are not encrypted thereby leaving the door open to data interception by cyber thieves (Heires, 2016; Livanis, 2016).

Eastin, Brinson, Doorey, and Wilcox (2016) pointed out a “privacy paradox” phenomenon whereby 70%-75% of consumers willingly share personal data in exchange for marketing incentives such as discount coupons, lower prices, and giveaways. However, consumers are unclear and uncomfortable about privacy issues with advertisers selling their personal data to third parties—thus incurring even more privacy issues when personal data continue to be sold off. Some respondents lacked an awareness of how valuable their personal information were to data brokers, and ultimately for Big Data analytics and data scientists in probing their very private backgrounds and personal lifestyles (Biswas, Pal, & Mukhopadhyay, 2016).

In a global study published by *Harvard Business Review* Morey, Forbath, and Schoop (2015) surveyed 900 respondents from five countries (US, UK, Germany, India, and China). The authors found that although customers were aware of releasing personal data in exchange for free apps and other free monitoring software, they were “deeply anxious” about how their personal information would be used. The authors advised that businesses would enhance customer trust and credibility with transparency by sharing how personal data would be used

and to allow customers control over the use of their data, while offering fair value to continue expanding a loyal customer base. Conversely, businesses that were not upfront about how they would be using customer data, were deceptive or unfair, or did not offer fair value, would end up fading into business oblivion by process of self-selection (Morey et al., 2015).

This same international study of five countries revealed that only: 27 percent of respondents were aware of personal data going public from social media network sharing; 25 percent from computer or device locations; 23 percent from surfing the Internet for information; 18 percent from web history logs; 17 percent from IP server addresses; and 14 percent from surfing the Web. The biggest concern (84% of Chinese, 49% of Indian respondents) was identity theft resulting from the misuse of personal data by businesses.

Concerning privacy issues, 80 percent of Germans and 72 percent of Americans worried about sharing their personal information. The most pressing privacy issues concerned government identification, health, and credit card information (Morey, et al., 2015).

In another 2016 global study regarding cybersecurity, the challenges faced by business leaders who were responsible for strategic and operational decision-making found 59 percent leveraged Big Data analytics to enhance cybersecurity measures and to reduce risks (PricewaterhouseCoopers LLC, 2016). The advantage in shifting to Big Data cybersecurity was the ability of real-time information in helping detect cybersecurity threats and risks before they happened. Big Data analytics were also employed by businesses to monitor employee online usage and to identify anomalous patterns of online use by employees. The most value was obtained from auditing, reviewing, and analyzing data points to gain insights towards better understanding who used data, how they did it, and when they used the data (Biswas et al., 2016; Farrow & Szanton, 2016).

PricewaterhouseCoopers LLC’s (2016) most recent worldwide study also found a 38 percent increase in 2015 of detectable cyber threats compared to 2014. The theft of intellectual property (IP) increased by 56 percent in 2015; and while employees were sources

of IP theft, 22 percent were associated with external business partners. Fifty-two percent of the businesses surveyed had implemented baseline security standards with partners and vendors. Moreover, these businesses increased their information security budgets by 24 percent, which resulted in a reduction of only five percent in losses. Increasingly, businesses were aware of the need for cybersecurity, with 58 percent having implemented an overall information security system. Apart from Big Data analytics cybersecurity strategies, businesses employed a variety of comparable digital security measures with: (a) cloud- enabled cybersecurity (69%), (b) advanced authentication (but no metrics were given, although this item was listed), and (c) collaborating with other businesses to improve digital security with proactive and resilient strategies (65%) (PricewaterhouseCoopers LLC, 2016). Additionally, the Federal Reserve Bank (considered the world’s premier bank) emphasized the need for more stringent cybersecurity for banks (Rosengren, 2016).

# Challenges of Using Big Data

As in every situation, the pros and cons involved in considering the myriad benefits of an innovation raises questions of what ethical constraints merit close examination and discussion. Rothstein (2015) urges:

Despite unique aspects, such as its data sources, scale, and open access provisions, the ethical issues surrounding Big Data are similar to those involving traditional biomedical research. Without question, the regulation of research can

be improved in many ways. The development of new analytical tools, however, such as Big Data, should not serve as a catalyst for abandoning foundational principles of research ethics. I continue to believe that respect for persons, beneficence, justice, and independent review are absolutely essential to the ethical conduct of research.

In developing countries where advanced digital technologies are scarce along with the supporting infrastructure needed for Big Data operations, a disproportionate exchange of Big Data is taking a paradoxical turn. The majority of lower-income populations in developing

countries use cellphones and smartphones to communicate and exchange information, thus inevitably contributing to the vast outpourings of unstructured data. However, because of the lack of IT and the availability of digital databases for Big Data analytics and applications, an ironic situation has developed for farmers in developing countries. Those who need the most help with predictive analyses (e.g. for agricultural production and weather-watching for real- time climate predictions) while at the same time also contributing heavily to the accumulation of unstructured data, are the ones who are least able to benefit from Big Data applications because of the lack of Big Data human resources, expertise, and infrastructure. Additionally, farmers in developing countries have fewer protective measures from data misuse compared to farmers in developed countries (Kshetri, 2014).

Big Data predictions are not infallible; for example, when predicting disease outbreaks. Google’s algorithms for predicting the avian flu in 2013 and the Ebola virus outbreaks in 2014-2015 were way off because ground conditions changed while the algorithms remained unchanged. The deterministic nature of modeling did not account for random interventions (Kugler, 2016).

On another note, Gudivara, Baeza-Yates, and Raghavan (2015) cautioned that the real test is to ascertain whether all business solutions need to employ Big Data when in fact the real issue is to find the right data sets. As Regalado and Watts (2014) also pointed out, the ideal is for business owners to know their operations inside out. Only from properly understanding their unique strategic and operational needs will business leaders benefit from Big Data applications to enhance decision-making.

# Summary

Overall, Big Data is a relatively new phenomenon since 2005 that is quickly gaining empirical validity and research traction. The first observation is that Big Data’s predictive value attracts business leaders, researchers such as data scientists, academia, and governments who are willing to pay for, plus mine, its expanding utilitarian applications (Arnus et al.,

2015; Cao et al., 2015; Flood et al., 2016; Hazen et al., 2016; Kshetri, 2014; Wang et al., 2016; Zhang et al., 2016). However, the second observation is the lack of data scientists available to perform Big Data analytics (Evans & Lindner, 2012; King, 2014; U.S. Bureau of Labor Statistics, 2016).

These two main reasons provide the purpose and the significance for this study to fill in knowledge gaps on Big Data analytics. The research goals of this study are to identify specific gaps in Big Data analytics for ongoing research in contributing towards knowledge expansion, to expand upon Big Data business applications for strategic and operational decision-making, and to examine the implications of Big Data affecting positive social change.

The next section, Chapter 3, will provide details of the methodological plan for the study. Given the main problem and identified gaps in the literature review, a qualitative case study will allow for an analysis to determine how, and in what ways, Big Data analytics can be developed to enhance strategic and operational decision making for business leaders. The next chapter will also describe the role of the researcher, participant selection process for the empirical phenomenological method employed, procedures for participation and data collection, plus the data analysis plan for the study.

# Chapter 3: Research Method

This study seeks to understand how the never-ending exponential explosion of structured and unstructured data in today’s digital economy affects business decision makers, and how business leaders can achieve optimal value from collecting and analyzing such large volumes of seemingly insignificant mega data to enhance their strategic and operational decision-making. This study examined how organizations are beginning to make the technological transformation from using traditional methods of decision-making based on traditional business analytics for strategic and operational decisions, in adopting more advanced digital approaches with Big Data analytics. The study will also consider the numerous challenges of using Big Data—including the management of large volumes of data, the types of data collected, challenges surrounding privacy, security, ethical issues, legal discovery, governance, and compliance. Finally, the study presented areas of opportunity to expand upon other areas of research affected by the escalating impact of Big Data analytics in assisting business leaders with their strategic and operational decision-making.

This chapter describes the rationale for using the recently introduced Interpretative Phenomenological Analysis (IPA) from Callary, Rathwell, and Young (2015). The methodological approach for this qualitative, open-ended, and semi-structured research study recognizes the IPA as a valid instrument facilitating research efforts to gain a better understanding of the overall concept of how Big Data affect the business environment through the perceptions of in-depth participant descriptions, opinions, and personal interpretations.

Participants were two business managers, two IT managers, and two data analysts who were current practitioners during the course of this study, and engaged in the newly emerging field of data scientists and Big Data analytics.

# Research Design and Rationale

The following research questions are proposed for the study. Based on an analysis of the problem and the purpose for the study, these research questions will explore how the new

and exponentially growing field of Big Data analytics and data scientists affect strategic and operational decision making for business leaders.

**General research question:** How do business leaders, IT managers, and data scientists analyze, use, and manage Big Data primarily consisting of unstructured data gathered from social media, sensor data, and GPS data (as distinct from more traditionally structured data accessed from data warehouses)?

The following research sub-questions expanded upon the general research question.

**RQ1:** How do business leaders, IT managers, and data scientists perceive Big Data (gathered from non-traditional and unstructured sources such as social media, sensor data, and GPS data) influence business and IT environments operations?

**RQ2:** How do business leaders, IT managers, and data scientists perceive Big Data (gathered from non-traditional and unstructured sources such as social media, sensor data, and GPS data) as influencing strategic and operational decisions to gain and maintain the competitive advantage?

**RQ3:** What do business leaders, IT managers, and data scientists perceive are significant challenges that Big Data (gathered from non-traditional and unstructured sources such as social media, sensor data, and GPS data) have on strategic and operational decision- making?

# Central Concept

The central concept of this research study was to gain a better understanding of the impact and challenges encountered by businesses in dealing with the newest data analytics phenomenon known as Big Data analytics. As business organizations strive to gain and maintain their competitive edge, Big Data will increasingly play in important role in all aspects of business decision making, including but not limited to supply chain management, human resources, finance and accounting, and marketing and sales (Davenport, 2015).

Big Data software models and open source resources and tools such as Hadoop play critical roles in Big Data analytics. However, these analytical digital processes require appropriate human capital resources such as data scientists who have been trained in various disciplines and methods to skillfully manage and analyze large volumes of structured and unstructured data (Evans & Lindner, 2012; Marr, 2015). These new processes, algorithmic tools, and software resources result in increasing productivity, new customer acquisitions, limiting customer churn, and in reducing inventory and product waste—to result in better profit margins, increased revenues, and thus, enhancing business shareholder value (Ali & Kid, 2014; Insider Retail, 2015; Whyte, Stasis, & Lindkvist, 2016).

# Research Design

The qualitative, open-ended, and semi-structured survey methodology based on the empirical phenomenological IPA approach was used in this study. This approach allowed the researcher the opportunity and access to probe more deeply into the lived personal and professional perspectives of Big Data practitioners. Such detailed descriptions of participants’ personal and lived experiences were expected and perceived to have been honestly conveyed to this researcher.

Survey questions designed by the researcher sought to uncover new insights from the six participants about their in-depth perceptions, descriptions, and experiences regarding this newly emerging topic of Big Data analytics. Such qualitative, in-depth descriptions would not have been possible with quantitative or mixed-methods approaches (Moustakas, 1994). Most of all the flexibility of a qualitative, open-ended, and semi-structured approach allowed this researcher authentic insights into lived experiences of data scientists and business and IT managers.

Quantitative research methods do not typically place an emphasis on the study of human behavior and lived experiences of participants, in contrast to interpretive phenomenological analysis (IPA) research studies (Callery et al., 2015). Furthermore,

quantitative designs often take into account larger sample sizes while attempting to study a narrower aspect of the research topic. In contrast, the IPA enables the researcher to observe the entire scope of the topic as described by participants, in order to better serve the goals of this research project with detailed and in-depth descriptions from participants (Callary et al., 2015). Hence, the obvious choice in selecting the qualitative IPA approach for this study.

# Rationale

The IPA approach used in this study examined the current and hands-on experiences of two business managers, two IT managers, and two data analysts to bring about informed research insights. Such insights included discovering the changing definitions, technologies, tools, and techniques associated with Big Data analytics. Therefore, the qualitative approach for the study was deemed more appropriate than quantitative research methods or the mixed methods approaches.

# Role of the Researcher

The role of the researcher in this study was primarily that of interviewer-observer. In this role, this researcher’s goal was to refrain from bringing unnecessary personal bias into the research, or by potentially exhibiting pre-determined outcomes or conclusions about research findings based upon personal experiences (from having reviewed the research literature, or from professional experiences as a data manager, or in a professional capacity associated with the subject matter). Big Data analytics being a relatively new and underdeveloped research topic of business intelligence, this researcher was committed to playing as unbiased a role as possible while observing and recording participant responses in studying their responses to Big Data analytics.

# Management of Bias/Relationships

This researcher has a professional background in managing data projects and data scientists, along with limited professional relationships with some of the study participants. This researcher’s goal was to maintain the highest ethical standards by removing all personal

biases and preconceived notions on the subject. The research participants were chosen based on their levels of professional expertise as Big Data scientists and practitioners; and from random selections and snowballing (the sampling method of a participant referring other possible participants to be interviewed). Whenever possible, this researcher avoided soliciting participation from potential participants who would be perceived to have unforeseen conflicts of interest or who would otherwise stand to gain from creating biased opinions for the study (such as data analytics software vendors and data sales and consulting services vendors).

# Other Ethical Considerations

Participation in the study was strictly voluntary with no monetary incentives or awards for participation. Participants provided responses to survey questions based on their own personal and professional experiences. Every participant provided their explicit consent to take part in the research study with the assurance that their participation and resulting individual responses would remain strictly confidential and anonymous.

# Methodology

The scope and depth of the research study specifically focused on studying and trying to understand the concept of Big Data as it pertained to ways in which it affected the business environment. Specifically, how Big Data affected strategic and operational decision making by business leaders. The rationale and approach for participant selection, recruiting procedures, data collection instrumentation, and the resulting data analysis plan are discussed below.

To avoid saturation responses, the sample size was determined by Mason’s (2010) and Moustakas’ (1994) recommendations to arrive at the optimal sample size of six participants for an in-depth study of this nature. Survey questions were designed to align with the qualitative research methodology of employing an open-ended, semi-structured interview approach, designed with the goal of contributing to expanding upon a greater body of knowledge on the subject of Big Data analytics. A goal of the survey design aimed for the feasibility of this research instrumentation to be easily replicated by other researchers, in the collective academic

research aspirations to develop new opportunities for ongoing, additional study by expanding on Big Data analytics research and in examining the implications for myriad social and business change impact.

# Participant Selection

The participant selection process for the research study specifically sought to align the scope, depth, and goal of the overall study as it pertained to the impact of Big Data upon the business environment and how business leaders were affected by Big Data analytics to enhance their strategic and operational decision-making. Furthermore, participants needed to have a baseline understanding of business data analytics in the business environment. Participants did not necessarily needed to be experts in the area of Big Data. However, selected participants needed to have a general understanding of how the growth, impact, and potential influences of Big Data would ultimately drive strategic and operational decision-making processes among business leaders.

The sample population chosen for this research study was limited to practitioners of Big Data analytics such as business managers, IT managers, and data analysts. All participants in the study were members of the online social networking site for professionals, LinkedIn. The job titles were general only in description, as similar titles continue to be designated across various industries in describing similar job functions concerning Big Data analytics.

Participants were selected and recruited from LinkedIn based on their experiences and understanding of business data analytics and Big Data’s impact upon business decision-makers. **Instrumentation, Participation, and Collection**

The instrumentation for this study consisted of: (a) one weeklong pilot survey posted online, on LinkedIn (the social networking site for professionals); 54 prospective respondents were invited to participate, from whom two persons declined and three responded; and (b) the open-ended semi-structured interview survey. The pilot was a short survey which asked the three research questions listed earlier. Responses received online by the researcher were from

participants who filled in their answers in blank spaces provided after each question in the pilot survey.

The open-ended, semi-structured research survey was longer consisting of seven questions that had been developed from the overriding research questions framing this study; they are listed in the Appendix. Sampling validity sought to avoid response saturation, with the sample size determined by Mason’s (2010) and Moustakas’ (1994) recommendations for in- depth interviews as adequate and relevant from between 5-25 qualified participants.

For this interpretive phenomenological analysis (IPA) study, six participants (two each of: business managers, IT managers, and data scientists) were recruited from LinkedIn, the online social networking site for professionals. This researcher personally conducted each survey via email communication with a qualified group of data scientists with LinkedIn profiles using SurveyMonkey. Participants were informed that they could skip questions or opt out at any time while taking the survey.

Each interview was recorded and dated to provide the necessary evidence that the interviews actually occurred, that participants had verbally agreed to be interviewed, and for their responses to be released for a dissertation research project on Big Data analytics and how this newly emerging data science affected strategic and operational decision making for businesses. No follow-up contact requirements were expected of participants. Participants received copies of survey responses and overall findings for the study.

Multiple data sources were considered for the study to analyze the findings. These ranged from the researcher as participant-observer and thus his perceptions, to the phenomenological lived experiences of two business managers, two IT managers, and two data scientists who were all involved in Big Data analytics activities during the time of this study.

The semi-structured approach encouraged flexibility for participant responses to be as honest and true as possible.

Participant responses were first received via email, then reviewed by this researcher, who recorded all responses into an Excel spreadsheet. These responses were analyzed according to numbered survey questions. This step was followed by categorizing responses according to salient descriptions and observations. These observations were further narrowed down to reflect dominant themes that emerged as credible themes that allowed for generalizing observations and applicable for further research that could be replicated.

To preserve anonymity and confidentiality, each participant was assigned a number; responses were coded according to each person’s assigned number. No computer software was used in coding participant responses. Member checks were carried out with participants to verify the authenticity of their descriptions and observations as perceived and recorded by the researcher. Participants were informed that their responses would be deleted after five years.

# Summary

The qualitative, open-ended, and semi-structured survey methodology afforded by the Interpretive Phenomenological Analysis (IPA) approach enabled this researcher to design a flexible instrument for gathering in-depth participant responses. This built-in flexibility also encouraged participants to be as honest and authentic as possible in describing and detailing their lived experiences as practitioners of Big Data analytics, regardless of whether they were data scientists or business and IT managers. Member checks communicated via email by this researcher allowed participants to further verify their responses as authentic, true, and honest.

All information gathered from participants were responsibly stored and solely used as credible data for research insights pertaining to this one study only. All information released by participants were not divulged, or sold, to other parties. The limitations of the study were entirely based upon responses conveyed by the participants, and as such were beyond the control of the researcher. The delimitations included sampling just six participants and not more, in order for the researcher to be more fully engaged in detailed and in-depth data

collection and analysis. Another reason for the small sample size was for the data collection process to be manageable, and to avoid response saturation from open-ended responses.

All participant responses served as research data gathered solely for purposes of this study. Salient observations that emerged were narrowed down, with these observations further distilled into distinctive themes. Distinctive themes that emerged were considered confident and credible findings; and that these findings could be generalizable in how Big Data analytics lent credence in enhancing strategic and operational decision making for business leaders.

# Chapter 4: Findings

The goal of this research study seeks to understand how the never-ending exponential explosion of structured and unstructured data in today’s digital economy affects business decision makers, and how business leaders such as CEOs, CIOs, and CFOs can achieve optimal value from collecting and analyzing such large volumes of seemingly insignificant mega data towards enhancing their strategic and operational decision-making. This study examined how professionals associated with gathering data intelligence for business research and development (R&D) in their organizations took steps in making the technological transformation from using previous methods of decision-making based on traditional business data analysis for strategic and operational decisions, into adopting more advanced digital approaches with Big Data analytics. Survey responses from six data intelligence professionals (two each from the disciplines of business management, IT management, and data science management) were illumining and varied for decision makers to better understand why and how businesses gain and maintain a competitive edge from using Big Data analytics. Survey responses further clarified: (a) the *need to understand* Big Data analytics for business leaders in their strategic and operational decision making; and (b) how *incremental and thoughtful steps* can assist decision makers to successfully implement Big Data analytics for actionable and effective results.

All survey participants for this study were male, and were executive-level decision makers within their respective business organizations. Although respondents were not required to state their age, they were at least aged 18 and over. Participants were from a pre-qualified sample population drawn from the professional social networking site, LinkedIn. A SurveyMonkey instrument was emailed to participants who responded via LinkedIn. These responses are included in the Appendix.

# Research Findings

Participant responses collected by this study uncovered four main themes for professionals to better adapt, adopt, and customize Big Data analytics to enrich and empower their respective businesses in gaining and maintaining a competitive advantage over competition. The main caveat that emerged was appropriately voiced by one participant who referenced the old saw embraced by carpenters to “Measure twice, cut once” in approaching Big Data analytics. Four main themes that emerged from these practitioners of Big Data were:

(a) specifying Big Data business goals, (b) developing value from Big Data, (c) Big Data quality and training, and (d) Big Data concerns regarding privacy, ethics, and governmental/legal compliance. All survey participants were from the Pacific Northwest region; five were from Portland, Oregon and one was from Vancouver, Washington. **Specifying Big Data Business Goals**

All participants were unequivocal in advising business decision makers to be very clear about what their business problem or problems were, first—before embarking on adopting Big Data analytics to resolve problem issues. In other words, decision makers needed to know and understand what their organizations were all about, inside and out first, before adopting Big Data analytics to better articulate and *specify their business goals* for adopting Big Data analytics. One participant stated the need in “understanding what is being looked for” which summarized the overall approach every business decision maker must take, in advance of deploying Big Data analytics, to enhance productivity and organizational effectiveness.

In most cases, this fundamental strategy in approaching Big Data analytics was proven even more valuable after gaining buy-in from decision makers in every department in the enterprise, in order for the new strategy of deploying Big Data analytics to become collectively actionable and thus to result in effective overall results for the enterprise. Input was vital from every department decision-maker, for the entire enterprise to be involved in collectively determining an effective plan to coordinate and implement Big Data analytics for strategic and

operational decision-making. One respondent warned, “Get the correct people involved, leave the ego behind, and remember why you are doing it.” A consultant advised, “Need to have executive buy-in and the ability for big data technical geeks to be able to translate big data speak into understandable and valuable business information sets.” In essence, decision-makers in every department had to perceive a collective utilitarian and unified value for implementing Big Data analytics to improve cost effectiveness and to enhance quality productivity.

# Developing Value from Big Data Analytics

Another participant offered the value of researching other businesses that had adopted Big Data analytics, to identify cost and other benefits, and for other insights on background and context in going with this new strategy. This same respondent urged, “Develop proof of concept to demonstrate value.” He also advised assessing Big Data analytics “from the industry perspective,” to learn about what these experiences were, to better inform those new to Big Data analytics. These tactics would serve to enhance buy-in from all departmental heads and decision-makers to adapt and implement Big Data analytics.

In addition to correctly identifying the problem question Big Data analytics would be used to resolving, it was also important to consider other variables. Such as: (a) to evaluate tools and technologies in selecting those that were most appropriate, (b) to determine if current data were available from trusted sources, (c) whether relevant data were captured, (d) how they would be measured for analysis, and (e) how to analyze and interpret the data. A participant cautioned, “Don’t forget about storage if hosted locally or the cost and security aspect(s) of hosting (data) in the cloud.”

In demonstrating proof of concept for value in adopting Big Data analytics, one participant who was a business manager suggested, “Start with areas of the organization that are more nimble and able to adapt to change (and free to make mistakes along the way).” Plus, begin employing Big Data analytics in areas initially deemed not strategic, “so as not to label the approach as negative irretrievably, in the event of a failure to get the results desired.” This

same respondent also warned businesses not to purchase Big Data apps sold with “the promise of many benefits to come.” The reason is because each organization is unique in setting their own business goals and in meeting preferred outcomes.

One participant who was a lead consultant for Fortune 500 clients in the Pacific Northwest of the US, with over 20 years of software experience specializing in Big Data engineering and solutions covering “a variety of product/program management, business development, and executive roles,” cited his company’s Silicon Valley Data Science (SVDS) guidelines for developing Big Data strategies. SVDS advocated designing and maintaining a data strategy that was actionable to meet current needs while also being adaptable to meet unforeseen and inevitable changes along the way (given that all businesses have to constantly face unpredictable variables impacting the business landscape). SVDS urged businesses to understand how to use Big Data as a company’s customizable resource in becoming successful and maintaining the competitive edge—instead of the traditional perception of viewing IT and data as service functions and therefore the need for forward-moving companies to very seriously consider implementing a Big Data strategy in transforming strategic and operational decision making.

# Big Data Quality and Training

The SVDS report referred to by the above-mentioned Fortune 500 consultant pointed out that in the past, IT and data were used as service functions. However, with Big Data analytics, raw data are now prized as strategic resources in creating more value for new products, increasing revenues, providing efficiencies, and in optimizing resource allocations. Big Data serves two important functions for an organization in: (a) articulating its value for the organization, and (b) in moving forward by providing a roadmap indicating how to proceed.

Another consultant participant insisted that “the data (be) of sufficient quality and timely” because “stale data” resulting from internal processing might have lost some potential data. A business manager for a power utility observed a specific customer-centric need for his

organization. “The main objective in using Big Data, essentially customer-provided data, is to help the customer and help the company by selling products and services. Predictive analysis also has (shares) these goals,” noted this power utility business manager. This business manager also noted that although the potential for data to be misused exists, “but at such high levels of detail and aggregation the ability and utility of doing so are essentially gone.”

Three out of six survey respondents mentioned the need for training. An information security engineer suggested data scientists should be provided with adequate training to more properly address how Big Data analytics can be deployed and optimized to resolve challenges. One consultant participant maintained that hands on, on-the-job training was important to understand infrastructure and in using large data sets to apply Big Data analytics. This same consultant also advised providing training “on risk-informed decision making and making sure that people are comfortable with new technology platforms including the cloud.” In line with the need for training, businesses would also need to develop “a culture that is open to change, and … an organization that supports R&D efforts which may or may not pan out,” observed another participant, an IT manager.

# Big Data Concerns Regarding Privacy, Ethics, and Compliance

Invariably, five out of six respondents voiced unanimous concerns regarding Big Data and privacy, ethics, and governmental/legal compliance. Organizations “need to ensure you are compliant with all legal ramifications, and in the event that any personal data is encompassed, ensure appropriate waivers are in place,” stated an IT manager. A business intelligence professional exhorted, “Activities should be bound by existing law (and) commonly accepted ethical standards.” An information security engineer averred that, “from my perspective I/we do because of security and compliance concerns.” “Personal information, commercially sensitive information, and cybersecurity are all concerns,” noted one consultant. However, a business manager found, “Data retention for compliance is a large problem, since data volumes

can exceed petabytes. Smaller aggregated data sets are better and adequate for compliance as long as they are representative of the base data.”

Perhaps one of the most cogent observations in adopting and adapting a Big Data strategy as suggested by the SVDS consultant is his company’s experience that it helps a business in better understanding the world. This is because a successful business is a smart machine that knows and understands how to react to volatile world conditions. Thus, in being able to understand and react accordingly to fluctuating conditions, a successful organization has the ability to come out ahead of competition—from using Big Data analytics to its advantage in meeting rapidly changing social-economic and business world conditions.

All four salient themes that emerged were distilled from participant responses reported in the following tables. Following the tables will be Chapter 5, in discussing findings reported in this chapter. The discussion in Chapter 5 will relate these findings and emergent themes to business and social change opportunities, plus offer suggestions and opportunities for further research.

|  |  |
| --- | --- |
| Respondent | Research Question #1 |
|  | Does your organization use Big Data Analytics? If the answer is no, please explain why not? |
| 1 | Yes, we are a consulting firm specialized in big data  analytics. We provide such capabilities to clients and use it ourselves. |
| 2 | No. Our source systems and analytic requirements  don’t support the need or feasibility at this point. |
| 3 | No. The company is slow to adopt new technologies and is budget constrained by virtue of being regulated. |
| 4 | Yes we are in the process of standing up Splunk. |
| 5 | Yes. |
| 6 | Yes. |

*Table 1.* Participant Responses to Question 1.

|  |  |
| --- | --- |
| Respondent | Research Question #2 |
|  | What is your background and/or training in data analytics? Also, please describe any training or experience specifically related to Big Data. |
| 1 | 20+ years in software with a specialization in big data engineering. Occupied a variety of product/program  management, business development and executive roles. |
| 2 | Limited. While I have worked with large data stores in both Data Warehousing and transactional systems, my experience in what I consider to be Big Data is limited to  some experimentation and prototyping in Hadoop. |
| 3 | Have experience in data warehousing and business  intelligence reporting as well as financial analysis |
| 4 | My background is related to reviewing traffic from  firewalls, antivirus, malware alerts for security purposes. |
| 5 | On-hands, on the job training. Understanding infrastructure and application ide of big data and working  with organizations with large data sets. |
| 6 | 20 years finance and 10 IT experience in large corporations. Implemented data dictionary, process modeling  and middleware teams in a large electric utility. |

*Table 2.* Participant Responses to Question 2.

|  |  |
| --- | --- |
| Respondent | Research Question #3 |
|  | Please describe in detail how your organization  uses Big Data analytics and list some benefits your organization has found in using Big Data analytics. |
| 1 | We have developed big data analytics proofs and research projects as part of our R&D program. We provide our Fortune100 clients in North America and EMEA with big data engineering solutions and data science  investigations. |
| 2 | Not currently using it. I could see potential value in  identifying fraud as well as finding efficiencies. |
| 3 | N/A. Company does not use big data at this time |
| 4 | We are in the process of standing Splunk up and implementing various sources for security purposes, we will be also reviewing data for compliance, network  utilization and more. |
| 5 | Large transmission company that uses bulk electric  system data for SCADA systems, monitoring and situational awareness. |

|  |  |
| --- | --- |
| 6 | Big data analytics are primarily used for electric power conservation, by helping customers manage date and time of consumption to better match output, especially during peak usage times. Predictive usage patterns are analyzed real time and customers alerted to reduce consumption in days ahead forecasting. Benefits include cost savings (not having to purchase excess power on the open market), reduction in peak demand (system stress reduced, system outages reduced), non-peak usage increases (maintains load on large systems that are not  scalable). |

*Table 3.* Participant Responses to Question 3.

|  |  |
| --- | --- |
| Respondent | Research Question #4 |
|  | What steps should businesses new to Big Data analytics (or if your organization would be new to using Big Data analytics) consider when deploying Big Data analytics to enhance their strategic and operational decision-making processes? Please explain the processes involved, including  pitfalls to avoid. |
| 1 | The state-of-the-art in the area combines two broad capabilities: 1. analytics platform engineering tools from the new media industry (open source parallel processing tools like Hadoop developed at Google, Facebook, Yahoo! etc.) 2. Data Science talent mixing mostly established advanced statistics practices and modern programming skills to leverage modeling at scale on the above platform tools and modern machine learning approaches. Successful organizations understand this pursuit ultimately requires the development of research organizations like those in the pharma industry (LT  investments with big payback at the end). |
| 2 | Clearly articulate the business problem, and show some  logical connection to how Big Data analytics can help solve it. |
| 3 | Assess big data from the industry perspective. Are others in the industry using it and what have been their experiences. Identify a business case, cost/benefit. What is the the question to be answered? Evaluate tools and technologies.  Does the data currently exist? Is it being captured? Develop proof of concept to demonstrate value. |
| 4 | I don’t know the specifics, it definitely takes planning and coordination in terms of what kind of data you want to be looking at, what exactly you hope to gain from looking at all this data, ensuring you have the right sources feeding your  aggregater. Don’t forget about storage if hosted locally or the cost and security aspect of hosting it in the cloud. |
| 5 | Provide some training on risk-informed decision  making and making sure that people are comfortable with new technology platforms including the cloud. |

|  |  |
| --- | --- |
| 6 | Be very specific about goals and objectives that will produce cost savings and new revenue immediately. Many big data apps are sold on the promise of many benefits to come; better to remain a little short term focused at the beginning.  Start with areas of the organization are more nimble and able to adapt to change (and free to make mistakes along the way) and areas that are not strategic (not at first) so as not to label the  approach as negative irretrievably in the event of a failure to get the results desired. |

*Table 4.* Participant Responses to Question 4.

|  |  |
| --- | --- |
| Respondent | Research Question #5 |
|  | What are some important steps and ideas to consider for analyzing Big Data findings? Please describe in detail what these steps are. |
| 1 | I don’t have enough time here. Sorry. Also not sure I want to share without knowing who is going to use this... |
| 2 | 1. Business requirements 2. Data Quality 3. Applicability of actual data/analytic output to the business problems being solved. |
| 3 | Define the questions to be answered? Identify the data and determine how to capture and measure it. Analyze and interpret the data. |
| 4 | Proper training for the analysts. |
| 5 | Understanding what is being looked for, ensuring that the data is of sufficient quality and timely. Stale data because of internal processes loses at least some of the potential data. |
| 6 | Always question the assumptions. Inherent biases can be self- fulfilling when so much data is available. Constructing the queries and interpreting results is still more an art. Data should be assembled into visual representations, since we are visual by nature. Results should be compared to historically known patterns to validate the data in a backcasting scenario. |

*Table 5.* Participant Responses to Question 5.

|  |  |
| --- | --- |
| Respondent | Research Question #6 |
|  | What privacy, legal, and ethical concerns should  businesses consider when using Big Data? Please describe in detail what these concerns are. |
| 1 | I don’t have enough time here. Sorry. Also not sure I want to share without knowing who is going to use this. |
| 2 | Need to ensure you are compliant with all legal ramifications, and in the event that any personal data is encompassed, ensure appropriate waivers are in place. |
| 3 | Activities should be bound by existing law commonly accepted ethical standards |
| 4 | I’m not sure about the question; from my perspective I/we do because of security and compliance concerns. |
| 5 | Personal information, commercially sensitive information and cyber security are all concerns. |
| 6 | The main objective in using big data, essentially customer provided behavioral data, is to help the customer and help the company by selling products and services. Predictive analysis also has these goals. Can the data be misused? Yes, but at such high levels of detail and aggregation the ability and utility of doing so are essentially gone. Standard corporate privacy and ethical directives apply and can be extended to specifically incorporate safeguards on corporate and staff use of data. Data retention for compliance is a large problem, since data volumes can exceed petabytes. Smaller aggregated sets are better and adequate for compliance as long as they are representative of the base data. |

*Table 6.* Participant Responses to Question 6.

|  |  |
| --- | --- |
| Respondent | Research Question #7 |
|  | What works well in creating, adapting, and maintaining strategic and operational processes to support decision-making driven by Big Data analytics—to more effectively achieve and maintain a sustained competitive advantage? Please describe in detail what these elements and  steps are. |
| 1 | I recommend an excellent SVDS paper on this topic (disclaimer: my employer but I still believe this is one of the best paper on the topic): <http://www.svds.com/building-experimental-> enterprise/ |
| 2 | Need a business sponsor, need a culture that is open to change, and need to have an organization that supports R&D efforts which may or may not pan out.. |
| 3 | Measuring performance against anticipated results and correlating to data analyzed. |

|  |  |
| --- | --- |
| 4 | Not sure, it’s like that old carpentry saying “measure twice, cut once” try to plan it out, get the correct people involved, leave the ego behind and remember why you are doing it. In my case is to protect people and the organization. |
| 5 | Need to have executive buy-in and the ability for big data technical geeks to be able to translate big data speak into understandable and valuable business information sets. |
| 6 | Central data modeling, including a data model repository, dictionary and associated structures are necessary to insure consistent architecture design and implementation. Combining data modeling with a strong process modeling requirement better documents the use of data in the organizations work flow. It is all too easy to degrade and lose key business intelligence without the data and process repositories. A full six sigma approach is best, but excellent process improvement results can be achieved with process improvement projects and the associated additions to the data and process repositories. Training is made easier going forward and personal changes do not result in the loss of functionality. |

*Table 7.* Participant Responses to Question 7.

|  |  |
| --- | --- |
| **In what city are you currently**  **employed?** | **Which of the following describes your job**  **function?** |
| Portland, Oregon | Consulting Lead (leading big data analytics engagements with F500 clients in the Northwest of the  US) |
| Portland, Oregon | IT Manager |
| Portland, Oregon | Business Intelligence Professional |
| Portland, Oregon | Information Security Engineer |
| Vancouver, Washington | Consultant |
| Portland, Oregon | Business Manager |

*Table 8.* Participant Location and Job Functions.

# Chapter 5. Discussion Overview

The goal of this phenomenological research study was to examine the Interpretive Phenomenological Analysis (IPA) lived experiences of executive-level Big Data analytics practitioners and their perceptions of using Big Data analytics to enhance decision-making by businesses leaders such as CEOs, CFOs, and CIOs. This research purpose and the research rationale for the study on this problem were primarily motivated by this researcher’s senior- level IT and data project management positions which revealed to him the current problem that most business executives were unaware of the potential benefits of using Big Data analytics to optimize strategic and operational decision-making. The researcher completed a detailed literature review to address each of the elements involved in this study in Chapter 2. The studies reviewed were relevant to the research question on how Big Data analytics can enhance strategic and operational decision making for businesses.

While the significance of Big Data only started impacting the business landscape from 2005 on, the biggest challenge today is for organizations to recognize the value of utilizing Big Data in enhancing quality productivity and maximizing cost efficiencies, from appropriately harnessing Big Data analytics that are unique to each business for strategic and operational decision-making. This paradigm shift redefines data analytics from using traditional databases structured upon Structured Query Language (SQL) offered by database systems such as Oracle, Microsoft Access, and IBM—to using Big Data analytics based on open-source adaptations from Hadoop. Big Data analytics are more targeted in optimizing decision-making results for real-time applications, among other benefits (De Mauro, Greco, & Grimaldi, 2015; [Giannakis](http://www.emeraldinsight.com/author/Giannakis%2C%2BMihalis), & [Louis,](http://www.emeraldinsight.com/author/Louis%2C%2BMichalis) 2016; Kitchin & Lauriault, 2015; Kshetri, 2014).

Survey responses from six executive-level data intelligence professionals (two each from the professional disciplines of business management, IT management, and data science management) further clarified two significant phenomenological discoveries and implications

for business decision makers to implement Big Data analytics as an organizational resource for ongoing business success. (Compared to considering IT and data as service functions as pointed out by Silicon Valley Data Services (2015) offered in a response from a study participant, a Fortune 500 consultant in data analytics.) In other words, the move to incorporate a Big Data analytics strategy within a business is a paradigm shift for corporations and even medium and small businesses to consider—which in of itself necessitates a leadership shift to recognize the benefits of using Big Data analytics. Thus, many business leaders and decision makers must instead reconsider business intelligence as is the norm today in using data sets from data warehouses or data marts, to using Big Data analytics as a strategic and operational resource that enhances decision-making.

Findings from this study showed that first, the *need is* for business leaders to: (a) *know their organizations inside-out* and (b) to *understand* how Big Data analytics can enhance their strategic and operational decision making capacities in realizing cost-savings while maintaining highest quality production outcomes. Second, how *incremental and thoughtful steps* involving consensus and buy-in from every departmental decision maker can assist decision makers in successfully implementing Big Data analytics for collective actionable and effective results to benefit the overall organization—from devising and designing a customized business data strategy affecting human resource considerations, marketing and sales, and product distribution.

After collecting the data, the researcher reviewed every participant response to understand the information that they had shared. The researcher further determined clusters of information that led to defining and constructing more salient themes that participants had articulated. Upon further iterations in reviewing and analyzing sub-themes, four main themes emerged: (a) specifying Big Data business goals, (b) developing value from Big Data, (c) Big Data quality and training, and (d) Big Data concerns regarding privacy, ethics, and governmental/legal compliance. All participant responses to the six open-ended survey

questions were recorded, and tabulated. Tables 1-8 in the preceding section, Chapter 4, reported verbatim all participant findings from the study.

# Discussion of the Findings

The overarching research question for this study was: How do business leaders, IT managers, and data scientists analyze, use, and manage Big Data primarily consisting of unstructured data gathered from social media, sensor data, and GPS data (as distinct from more traditionally structured data accessed from data warehouses)?

Research findings from this study fully corroborated numerous other studies cited in Chapter 2 on the Literature Review and as well, this researcher’s own first-hand experiences as a senior IT program manager for the largest athletic supply corporation, Nike, Inc. For instance, Banks (2016) and Whyte, Stasis, and Lindkvist (2016) had noted how executive-level decision makers are quite unaware of the benefits of exploring Big Data analytics and that adopting and adapting this new business strategy unique to their own business goals would be beneficial in enabling their companies to become even more successful businesses. In fact, Big Data analytics tapping into vast repositories of never-ending raw, unstructured data would enable CEOs, CFOs, and CIOs to find advantages such as analyzing real-time results and thus, apply results-driven innovations to come out ahead of competition in attracting and retaining customers (Davenport, 2014; Hazen et al., 2016; Zhang et al., 2016).

However, in mitigation, it is reasonable to point too, out that Big Data analytics is a relatively new science. Only since 2005 has this nascent digital frontier been gradually gaining traction and recognition for its valuable contributions to every facet of organizational and social-economic-scientific operations. As noted by Ali & Kidd (2014), similar implications and ramifications are also important for non-business sectors to consider, e.g. government agencies, academic and think tank research facilities, and the nonprofit sector (or the third sector of the economy).

Research findings from this study have added to and expanded upon the currently exploding information and knowledge base of how Big Data analytics can enhance strategic and operational decision making for every level and area of business endeavor. Therefore, this researcher’s mission is to continue communicating the important and significant role Big Data analytics plays (in contrast to traditional data analysis that most businesses are currently employing) to more properly enhance strategic and operational decision making for business leaders. (This researcher is in the process of writing his first book on this topic.) It is an imperative for the majority of business leaders to become aware of, and thoughtfully implement, Big Data analytics to stay in business as successful enterprises. This observation is especially relevant given “Moore’s Law” which shows the power of computer processing doubling every 18-24 months. As an aside, Gordon Moore was a co-founder of Intel, the microchip processor. Moore’s observations have fueled the ongoing reference to Moore’s Law by IT and computer scientists, engineers, and data scientists. As in the case of the exponential speed of powerful computer processing capabilities and data growth brought on by unstructured data and structured data; and as evidenced by the newly emerging financial technical industry, or “fintech,” as it is called from having developed its own sub-specialty in amassing financial data brought on by IT and data developments (Kirilenko & Lo, 2013).

# Findings in Light of the Research Question

The primary research question for this study was: How do business leaders, IT managers, and data scientists analyze, use, and manage Big Data primarily consisting of unstructured data gathered from social media, sensor data, and GPS data (as distinct from more traditionally structured data accessed from data warehouses)? For purposes of this study, the term Big Data analytics was defined as consisting of raw, unstructured, and messy data—from which the process of repetitive mining of data points eventually yielded more structured and definitive targeted results for problem-solving. For instance, the literature review in Chapter 2 reported that then 17-year-old Brittany Wenger won Google’s 2012 Science Fair Grand Prize

Winner worth a $50,000 college scholarship plus other perks. Wenger, after 7.6 million trials, developed a software program that can identify breast cancer biopsies with 99 percent accuracy (Borel, 2013; Marr, 2015).

# Big Data Analytics is Valued for Business Decisions

The overarching finding from this research study was that every participant urged business decision makers to be very clear about what their business problem or problems were, first—before embarking on adopting and adapting Big Data analytics to resolve each unique problem issue. This corroborates Roubelat et al.’s (2015) recommendation; e.g., of social media exchanges being valuable data points for business insights. Such unstructured, raw nuggets of Big Data are valuable data are priceless to mine continuously, to discover ever-

changing consumer trends and behavior—for business leaders who value the goal of optimizing business profits.

However, the observation of this researcher which motivated him to undertake this study has been his decade-long observation that business leaders are unaware or unable (e.g., because of scarce resource allocations in terms of funding or personnel and other limitations) to maximize the myriad benefits bestowed by Big Data. Even more revealing is the fact that not all decision-makers in an enterprise welcome innovative ideas in getting ahead; hence the need for buy-in from every decision maker in the enterprise. For instance, a consultant participant in the survey suggested the “need to have executive buy-in and the ability for big data technical geeks to be able to translate big data speak into understandable and valuable business information sets.” One participant, a business intelligence executive, stated the need to “develop proof of concept to demonstrate value” plus the need to “assess big data from the industry perspective.”

# Need for a Paradigm Shift to Optimize Big Data Business Analytics

Another participant (an information security engineer) advised, “It’s like the old carpentry saying ‘measure twice, cut once.’ Try to plan it out, get the correct people involved,

leave the ego behind and remember why you are doing it. In my case (it) is to protect people and the organization.” In other words, a cohesive approach is essential for all decision makers within the company in understanding the need for exploring Big Data analytics. It is also imperative for business leaders advocating Big Data analytics to be able to explain in “non- geeky” terms how this new approach will benefit the entire organization.

Similar concerns of not using data smartly are prevalent in other diverse industries such as the oil and gas industry—where Big Data has the potential to reshape the entire industry (Perrons & Jensen, 2015). Findings from this study also underscore and suggest a similar need for a cultural overhaul within business organizations determined to stay in business for the long haul. Wherein flexibility and adaptation in welcoming changes that are vital to repurpose and align business goals to staying successful and profitable are proposed by leaders that are adapted and accepted with buy-in from every department within the organization. So too, by extension, the need for every industry to consider the burgeoning role of Big Data analytics that no industry can escape from—given the never-ending mass proliferation of unstructured and structure data.

Hence, strong business leadership (including leadership in government and nonprofit agencies) is instrumental to clearly articulate and persuade buy-in for stakeholders. The array of stakeholders range from in-house decision makers to industry partners such as vendors and even persuading and assuring consumers about the safety of their personal information released to the company.

# Strong Leadership is Essential to Adopt and Adapt Big Data Business Analytics

In adopting Big Data analytics for business, the important point to emphasize is the imperative for enterprise leaders to understand their own organizations inside and out first, before deploying Big Data analytics to meet business goals and/or problem-solve issues such as inventory control or increasing marketing and sales. Such a paradigm shift to consider Big Data’s challenges in affecting the strategic and operational operations of an organization

necessitates behavioral changes in the education and the mental modification and acceptance of CEO, CIO, and CFO mindsets (Winthrop & McGivney, 2016). Without strong leadership at the helm, attempts to integrate Big Data business analytics may not be a worthwhile endeavor to consider, as the Fortune 500 consultant advised in his survey response.

For example, this Fortune 500 respondent cited his company’s position paper on developing a data strategy that any business leader can implement. Important items to consider include considering the business objectives of a company—which would become the goals of the data strategy. Second, keep the adoption and adaptation process moving by developing tactics based on achieving the main business goals. Third, include all stakeholders in the organization to consider all possible points of view, and as important, for buy-in by all stakeholders as well. Fourth, review and analyze how data technology can assist in the process of developing a data strategy. Fifth, consider where common relationships exist, and how efficiencies can be consolidated to further parlay company resources, to result in gaining more valued outcomes. Sixth, since not all projects are or have been created equal, ask which ones matter most, in order to define and figure out where and when to start the strategic process.

Seventh, as in planning a successful road trip, define this roadmap with a destination that allows the goal or goals to be achieved with accountable benchmarks or milestones, towards an end-point(s). Most important, recognize that having developed a data strategy is not an end-all in of itself. Rather, the dynamics of exponential data explosion and accumulation require a business leader to continuously revisit, refine upon, and reuse this strategy in light of changing, volatile, and unpredictable conditions to stay continuously fresh and refreshed with insights benefitting the company on its journey to stay relevant and ahead of competition.

# Implications for Business Applications and Social Change

This study was not predicated on any single or combined Big Data analytics theoretical framework(s). Rather, this research study was undertaken to explore the nascent science of Big Data analytics just now beginning to be recognized for myriad valued contributions as

organizational resources instead of the current employment of IT and data collection in providing service functions as suggested by Silicon Valley Data Services (SVDS, 2015). Furthermore, there are no theories on Big Data analytics at this early stage of its development.

Therefore, the overarching research question asked: Why are so many executive decision-makers unaware of, or are seemingly unprepared for, the critical need to switch from today’s business data analysis to harnessing Big Data analytics for cost-effective operational strategies and decision-making? What insights do data scientists and business managers suggest are timely issues and interventions for business leaders to consider? How can businesses transition as seamlessly as possible into harnessing Big Data analytics for effective strategic and operational decision-making?

# Theoretical Implications for Big Data Business Applications and Social Change

Rather, Peter Viall’s (1986; 1998) High Performance Systems (HPS) theory is an appropriate business theory to reference for this study. HPS has guided the development of this study’s conceptual framework, and as well, in analyzing the phenomenological lived findings of participants involved in this study. To reiterate, HPS theory explains how high performance teams and organizations are more proficient and efficient in producing outstanding business results from team efficiencies and enhanced productivity from using smart strategic and operational decisions envisioned by team leaders and members—and continue to thrive in the face of all odds. Moreover, this seminal business theory continues to be widely referenced by business startups even 30 years after its introduction (Viall, 1986).

For example, the need for an enterprise to function cohesively as one stellar, successful company necessitates the cooperation and buy-in of all decision makers to embark on and deploy every new business or organizational strategy. As Janz’s (2014) ongoing research showed highly motivated business teams working on a great product had the potential to self- destruct if a cohesive team spirit did not evolve to enable group members to work together constructively while adopting new ideas. Therefore, the emphasis that survey participants had

placed on collective agreement and buy-in from decision makers supports Viall’s theory (1986, 1998). That is, for a business to successfully adopt and adapt Big Data analytics, the entire company from decision makers on down to line employees must understand the need to incorporate this new strategy; plus the need to customize accordingly to changing conditions in order for the company to function effectively with cost efficiencies and quality productivity.

Janz (2014) had adapted Viall’s HPS theory in studying highly motivated technological startups; he called them High Performance Teams (HPTs). HPT team members were highly satisfied with perceptions of their own personal performances and overall satisfaction as being a team member. Inevitably, HPT teams perceived a solid, common purpose that every member strived to achieve and maintain; were very collaborative with a common identity; possessed complementary skills among team members; and exhibited a high sense of autonomy with team members rotating as leaders. These HPT findings are congruent with this study’s findings whereby participants stressed the need for collective agreement in implementing a new strategy such as Big Data analytics.

# Practical Implications for Big Data Business Applications and Social Change

This study confirmed research results and findings reported and presented in Chapter 2 on the review of the literature. Such collaborative team-building strengths resulted in superior outcomes for businesses, noted Janz (2014). In defining Big Data scientists, the U.S. Bureau of Labor Statistics (2016) also expressed similar requirements. Big Data scientists need to possess cross-disciplinary adaptability and collaborative skills in addition to being productive team members solidly working together on one big project with a common goal.

The practical implications of hiring collaborative data scientists is an important business strategy for a company’s human resource department to know of, and to carry out with due diligence in filling Big Data positions as seamlessly as possible. However, the wrinkle is, a recent LinkedIn survey of 291 hiring managers showed 58 percent found the lack of soft skills in candidates hindered hiring (Davidson, 2016). In this same *Wall Street*

*Journal* article (8/31/16), a *Wall Street Journal* survey of 900 executives found 92 percent indicated soft skills were equally or more important than technical skills; with 89 percent finding it difficult to locate qualified applicants to fill positions—and that the problem spanned age groups and experience levels. Soft skills are defined as the ability to communicate clearly and effectively, the ability to get along well in teamwork, being punctual, possessing critical thinking skills, sociability, creativity, and adaptability (Davidson, 2016).

Therefore, in addition to technical skills, data scientists need to develop social and critical thinking skills to be employable. A goal of this researcher is to communicate this dire business situation while raising the banner on incorporating Big Data business analytics to businesses large and small. A book project is in process to pave the way for business decision makers to become aware of the related and anomalous situations of Big Data analytics facing business leaders. It is imperative for business leaders to be aware of such related and situations confronting the adoption of Big Data business analytics—and to have the vision and determination to steer change towards accepting this increasingly important scenario impacting the business landscape. With strong leadership capabilities, the accompanying benefits of steering a turnaround in social change attitudes to adopt Big Data analytics as a valued business resource can also enable more functionality and enhance productivity.

Hence, the need is to educate business leaders on how to integrate Big Data in incremental and thoughtful ways, while also helping them understand some related issues facing in-house departments such as human resources. Another related challenge is how bias can be introduced unconsciously into algorithms by software developers when aggregating data. One Microsoft researcher noted that machine learning technology developed by white guys became “Artificial intelligence’s white guy problem” (Crawford, 2016). This problem was reflected in algorithms that inappropriately built in sexism, racism and other discriminatory forms; e.g., Google’s photo app that recognized black people as gorillas and

Hewlett-Packard’s webcam software could not clearly identify people with dark skin tones. The explanation given was, when algorithms were digitally trained only on recognizing images of people who were overwhelmingly white, then the software would have a harder time recognizing non-0white people (Crawford, 2016).

Like any new technology, Big Data analytics can be a boon if applied appropriately.

However, if data scientists are not trained to enlarge their worldviews to accommodate a wider business and/or demographic landscape, embarrassing mistakes will erupt. Hence the ethical consideration and need to learn from initial mistakes, while staying on course with timely feedback and appropriate revisions (Wang et al., 2016).

# Limitations

In identifying limitations, it is hoped these items will assist other researchers carrying out similar or replication studies to improve upon this study. Most notably, based upon the sample population that was available to qualified respondents contacted through the professional networking site LinkedIn, all respondents were male, and were also exclusively “white guys.” It is this researcher’s hope that future phenomenological studies will have the capability to include female and minority respondents, too.

Time constraints necessitated participants to respond via email, which was facilitated by ease of participation through SurveyMonkey. There could be more options to build in survey instrumentation such as phone interviews and mailed questionnaires. Additionally, with Big Data analytics being such a nascent discipline of inquiry, options to enlarge the sample population were limited by necessity.

# Conclusions

Even though Big Data analytics is relatively new, business leaders with the vision, foresight, and the acumen to thoughtfully optimize artificial intelligence for highly targeted results have found that employing this strategy is indeed to their profitable advantage. Take for example, Armancio Ortega, CEO of the Spanish high street fashion house, Zara. Instead of

worrying about inventory control, overstocks, and having to dispose at a loss fashion styles that sold poorly, Zara has leveraged Big Data analytics to predict saleable fashion styles with financial aplomb. Ortega is the world’s second richest person, after Bill Gates (Vinton, 2016).

In a 2015 survey conducted by Microsoft and Telsyte with over 300 Australian retailers, almost half of the merchants indicated they would utilize the Internet of Things (IoT) within the next two years (Inside Retail, 2015). The Australian retailers gave three reasons for deploying Big Data analytics: (a) cost savings, (b) increasing revenues, and (c) productivity benefits. Additionally, 28 percent retailers experienced cost reductions in their daily operations.

In the area of healthcare, England’s Aviva, a large insurance company, has developed algorithms to analyze consumer credit reports and marketing data, resulting in high probability analyses that are capable of identifying and predicting health risks of potential insurance applicants. The added value of Big Data comes from not only monitoring customer relationships, but also in finding patterns from unknown variables that end up accurately foretelling consequences of prospective customers (Perrons & Jensen, 2015). On the other end of predictive analysis, business leaders can generally depend upon Big Data analytics to project business growth, anticipate and prepare for mitigating conditions in the event of catastrophes (whether climate, terrorist, or otherwise), and remain on top of adverse conditions as much as possible (Harbor Research, 2016).

The customer-centric business model facilitated by the Internet’s 24/7 easy access and convenience is a growing marketing strategy fast gaining traction. Business owners can capitalize on increasing brand awareness with prospects (through word-of-mouth advertising and web surfing) and targeting repeat customers at every moment with an online retail presence. The goal and the answer are simple in every case—to problem solve challenging business situations, with the goal of achieving enhanced decision-making, resulting in valuable outcomes and successful solutions for businesses and individuals (Regalado & Watts, 2014).

# Recommendations for Further Research

Big Data has taken an amazing futuristic turn on consumer-centric marketing in deploying simplicity, speed, and storytelling for businesses to churn the wheels of traditional commerce into even bigger, faster profits via the V’s of velocity, volume, and variety. King (2014), director of Harvard University’s Institute for Quantitative Social Science noted no area or discipline will be left untouched by Big Data. As is true for almost all facets of life, those with the vision and business acumen to recognize the myriad benefits of Big Data will be rewarded.

One area of research that profitably deploys Big Data analytics is England’s Aviva health insurance conglomerate in taking the initiative to screen prospective healthcare patients using predictive analysis. Another area of positive intervention in using Big Data predictive analytics is in education to help lower-income students stay in school and not drop out (Sax, Kanny, Riggers-Piehl, Whang, & Paulson, 2016). Even in writing bestselling books, a new book on using Big Data algorithms shines a light on successful tactical ingredients. *The Bestseller Code* (2016) by Jodie Archer and Matthew L. Jockers lists bestselling content touch on: work, life in the classroom (not campus parties), dogs (not cats), and laboratory (more compelling than church). Most of all, bestsellers are grounded in reality and easily connect with readers, while subjects and not genres more adroitly connect with readers, as these two authors found.

It is inevitable for Big Data to influence all aspects of consumer marketing and production even as consumers themselves are writing the code on their preferences and what appeals to their sensibilities. As water flows from higher to lower levels, businesses that start using Big Data analytics now will reap the benefits trailblazers enjoy. However, as a respondent noted, “Measure twice, cut once” in being very clear about how to apply Big Data analytics.

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Appendix A: Survey Questions

1. Does your organization use Big Data Analytics? If the answer is no, please explain why not?
2. What is your background and/or training in data analytics? Also, please describe any training or experience specifically related to Big Data.
3. Please describe in detail how your organization uses Big Data analytics and list some benefits your organization has found in using Big Data analytics.
4. What steps should businesses new to Big Data analytics (or if your organization would be new to using Big Data analytics) consider when deploying Big Data analytics to enhance their strategic and operational decision-making processes? Please explain the processes involved, including pitfalls to avoid.
5. What are some important steps and ideas to consider for analyzing Big Data findings? Please describe in detail what these steps are.
6. What privacy, legal, and ethical concerns should businesses consider when using Big Data? Please describe in detail what these concerns are.
7. What works well in creating, adapting, and maintaining strategic and operational processes to support decision-making driven by Big Data analytics—to more effectively achieve and maintain a sustained competitive advantage? Please describe in detail what these elements and steps are.

Appendix B: Curriculum Vitae

Donald Lee Jr. MS, MBA, PhD [donlee98@yahoo.com](mailto:donlee98@yahoo.com)

|  |  |
| --- | --- |
| **EDUCATION:**  PhD Management – Management.......................................... | 2016 |
| Calamus University, London, UK  Dissertation Topic: Big Data Challenges: Enhancing Strategic & Operational Decision Making for Business  Dissertation Advisor: Dr. Morris Berg |  |
| Master of Business Administration ................................................. University of Phoenix | 1998 |
| Master of Science – Computer Info. Sys. .....................................................  University of Phoenix | 2001 |
| Bachelor of Science – Education.........................................................................  University of Phoenix | 1997 |

**PROFESSIONAL EXPERIENCE:**

Senior IT Program Manager ....................................... 2016-Pres.

Nike Inc., Beaverton, OR

x Senior IT Program Manager for Nike’s Americas territory; managing a portfolio of major projects for multiple business units and corporate brands.

x Lead project teams incorporating resources worldwide to deliver enhancements and support for critical business operations including major infrastructure build-outs, system enhancements, and technology support for world-wide product distribution centers.

x Consulted for senior management across business platforms and brands such as Converse to leverage best practices for all business aspects.

x Delivered highly visible reports and presentations to executive management at the program level on time sensitive events such as the 2016 Olympic Games in Brazil.

x Managed multiple vendors concurrently with corporate sourcing and procurement resources to ensure delivery of projects while mitigating contract and logistical risks.

Senior Project Manager ...................................................... 2015-2016

Standard Insurance, Portland, AZ

x Senior Project Manager for multiple development and infrastructure projects for the replacement and upgrade of legacy systems and applications for a major corporate systems security and modernization initiative.

x Managed both strategic and tactical activities of internal resources and multiple vendor resources.

x Collaborated across multiple business units to build collaboration and consensus and minimize impact to daily business operations while meeting key project

milestones and deliverables on time and on budget.

x Use of multiple project management tools and software while implementing standard software development methodologies to deliver complex projects on time, within budget, and within the defined scope.

Senior Project Manager 2010-2015

Portland General Electric, Portland, OR

x Senior Project Manager for development and implementation of IT and Corporate projects. Managed cost, schedule, and performance of complex projects involving multiple stakeholders across all levels of management.

x Managed and delivered application development, IT Infrastructure, demand side management projects, and business process improvements for customer energy resources while working collaboratively across the organization.

x Managed IT and Corporate Security initiatives for Data Loss Prevention and implementation of corporate-wide security and encryption tools.

x Use of both Agile and Waterfall project management and software development methodologies to deliver complex projects on time, within budget, and within the defined scope of requirements.

x Managed projects leveraging PGE’s AMI technology and worked closely with Network Data Operations to launch new utility products such as Critical Peak Pricing for residential customers and other demand side management projects for PGE’s business customers.

x Managed corporate-wide initiative to migrate from Windows XP desktop operating system to Windows 7. This project included a full inventory, analysis, and remediation of legacy technologies and applications across all business divisions.

x Managed the upgrade of PGE’s call center technologies including call recording technologies and call quality assurance systems.

x Managed the design and deployment of new Cisco VoIP technologies to all company locations across the state of Oregon. Worked with vendors to acquire, sequence, and test, and deploy with unique requirements for each site.

x Managed all technology aspects new building site construction by working with construction project managers, facilities planning, IT Infrastructure teams, and executive management.

Manager Systems Analysis & Dev 2009-2010

Pacific Power, Portland, OR

x Led systems development and support of utility outage management systems including ABB CADOPS, DMS, and supporting outage management reporting systems.

x Led GIS, EDI, and Application Integration teams supporting vendor platforms such as ESRI, Tibco, and IBM.

x Led new project initiatives to replace existing technologies and enhance current technologies using formal project lifecycle methodologies to achieve overall cost, schedule, and performance objectives.

x Managed and regularly reported on compliance activities related to SOX, FERC, and NERC CIP requirements.

x Worked with and coordinated all areas of IT to develop and maintain application reliability standards, system scalability, and total cost of ownership for IT assets.

x Worked closely with system architects and vendors to evaluate technology solutions and define technology roadmaps.

x Led and participated in Disaster Recovery planning exercises.

x Developed and implement technology obsolescence and application release methodologies to maintain service level agreements and total cost of ownership for IT assets.

x Led both staff level and management level personnel with a team of 30+ FTE and contract employees.

x Managed IT capital and expense budgets exceeding $50 million dollars.

Manager SAP Basis/Ent Apps 2004-2009

PacifiCorp, Portland, OR

x Led SAP Basis and SAP Security teams to a multi-landscape SAP ERP environment.

x Led SAP infrastructure and software upgrades including support pack deployments, system tuning, and integration with other SAP and third-party vendor software, middleware, and hardware.

x Led SAP Security re-engineering and re-design projects to comply with SOX and General Computing Control requirements.

x Led compliance and audit activities to ensure compliance with FERC, NERC CIP, and SOX requirements.

x Led new initiatives and activities related to the design and deployment of load balanced, clustered JBOSS and SAP WAS infrastructure.

x Led the design and deployment web infrastructure for SAP and other J2EE applications in a clustered environment with failover across data centers.

x Led a team of 60+ FTE and Contract employees supporting middleware applications, enterprise content systems, and enterprise data warehouse.

x Liaised with customers in gathering requirements for new applications.

x Designed and deployed IT infrastructure solutions to support various stages in the systems development cycle.

Manager, Network & Infrastructure Services. 1999-

2004 PacifiCorp, Portland, OR

x Led IT Infrastructure Project Management team including hiring, program management leadership, and assignment of project management resources such as project managers, business analysts, telecom analysts, administrators, coordinators, and technical writing/documentation specialists.

x Led efforts in process and quality improvements for corporate project life cycle methodologies.

x Managed multiple projects to implement new enterprise distributed systems monitoring capabilities modeled after Novell’s Global Network Operations Center (GNOC) using a combination of best-of- breed tools and technologies.

x Implemented technologies to support event correlation for distributed systems monitoring.

x Worked with system architects, systems/network monitoring specialists, and vendors to develop complex end-to-end and transactional monitoring using Vital Suite.

x Managed Y2K projects to develop system gap analysis and remediation processes.

x Participated in Disaster Recovery planning and implementation for Survival Critical and Mission Critical applications.

x Managed billing functions for corporate telecommunications infrastructure and multiple locations throughout a six-state service territory.

x Led activities related to telecommunications billing/invoice auditing, telecommunications billing reconciliation, and disputes.

x Designed and led cost recovery and expense management activities for all corporate telephony and wireless expenses.

x Led project to implement new telecom expense management system to drive overall cost savings exceeding $1M dollars of corporate network and telephony expenses.

x Led vendor management activities including vendor contract negotiations, RFP/RFI process, and development of new service level agreements.

x Responsible for $50 million in combined capital and expense budgets and 20+ full-time and contract employees.

Cryptologic Officer, 1990-2010

United States Navy, USA

x Technical lead for development and implementation of cryptology systems, tools, and techniques for national defense initiatives and directives.

x Led both enlisted and officer personnel to produce client requirements and deliver cryptology services for national intelligence consumers.

x Operated highly classified and sensitive computing and crypto technologies to produce timely intelligence data for Naval assets and national intelligence consumers.

x Deployed globally to support Naval platforms and the National Security Agency.

**CERTIFICATIONS:**

LAN/WAN Networking, Leeward Community College, 1996

**PROFESSIONAL AFFILIATIONS:**

Society of Information Management Regional Leadership Forum, 2008

Society of Information Management Leadership Development Round-table, 2009

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