Managing Data-Driven Change: A Model of Unintended Deviation

Sang-Mun Ray Cho
findraycho@gmail.com

Follow this and additional works at: https://digitalscholarship.unlv.edu/thesesdissertations

Part of the Business Administration, Management, and Operations Commons, and the Work, Economy and Organizations Commons

Repository Citation
https://digitalscholarship.unlv.edu/thesesdissertations/3481

This Dissertation is brought to you for free and open access by Digital Scholarship@UNLV. It has been accepted for inclusion in UNLV Theses, Dissertations, Professional Papers, and Capstones by an authorized administrator of Digital Scholarship@UNLV. For more information, please contact digitalscholarship@unlv.edu.
MANAGING DATA-DRIVEN CHANGE:
A MODEL OF UNINTENDED DEVIATION

By
Sang-Mun Cho

Bachelor of Arts – Communication Arts
University of Wisconsin, Madison
2001

Master of Business Administration
Master of Science – Hospitality Administration
University of Nevada, Las Vegas
2010

A dissertation submitted in partial fulfillment
of the requirements for the

Doctor of Philosophy – Hospitality

Hospitality Management
William F. Harrah College of Hospitality
The Graduate College

University of Nevada, Las Vegas
December 2018
This dissertation prepared by

Sang-Mun Cho

entitled

Managing Data-Driven Change: A Model of Unintended Deviation

is approved in partial fulfillment of the requirements for the degree of

Doctor of Philosophy – Hospitality
William F. Harrah College of Hospitality

Brett Abarbanel, Ph.D.
Examination Committee Chair

Bo Bernhard, Ph.D.
Examination Committee Member

Anthony Lucas, Ph.D.
Examination Committee Member

Glenn Nowak, M. Arch.
Graduate College Faculty Representative

Kathryn Hausbeck Korgan, Ph.D.
Graduate College Interim Dean
Abstract

Data-driven change in hospitality gaming is desirable because of the opportunities to leverage untapped sources of rich and abundant marketing data. However, change has been difficult to implement as indicated by a lack of widespread adoption. Some have attributed these difficulties to cultural, structural, and other generic factors but these explanations fail to explain the root dynamics of data-driven change.

In this dissertation, it is theorized that data-driven change requires a particular form of social interaction, which are called analytical bonds (AB). The suggestion was that there is a sender of an analytic deliverable and a receiver that makes a decision, and that the sender and receiver do not hold the same level of formal power. To study these bonds, a broader qualitative design of grounded theory was applied to interview data from industry leaders. The resultant model of unintended deviation (MUD) explained that the difficulty arose from a deviation from the company's intended path towards data-driven change. This deviation stemmed from survivalistic overprotectionism—an organizational behavior where actors work in a self-interested manner and provide a facade of informed analytics by exuding a belief in data-driven ideals to top management. This was shown to work in opposition to behaviors that are facilitative of analytical bond growth.

The construct of analytic facilitation (AF) was also introduced and represented the activities and behaviors that builds ABs and different individuals demonstrate AF to varying degrees. An embedded instrument was used to measure for AF. As a pilot study, AF was distinguished from knowledge sharing via a factor analysis, and report usage showed initial promise as a means to measure AF via a regression model. Applying the MUD and considering AF, AB, and existing understandings on silo effects, the theory can help leaders to make informed decisions around analytics that prevent deviation and provide corrective action.
Acknowledgements

This dissertation was made possible through the continued support from my committee: Dr. Brett Abarbanel (chair), Dr. Bo Bernhard, Dr. Tony Lucas, and Glenn Nowak. A special thanks also goes to Dr. Kahlil Philander who was instrumental in laying a path for me to pursue a doctorate. I would also like to thank Frank Riolo for his mentorship and for believing in research. Above all, Salma Ettefagh has been by my side every step of the way; through thick and thin, her love is enduring.
Dedication

To the scholars in my family that have come before me. To my father, Dr. Lee-Jay Cho and to my brother, Dr. H. Jeremy Cho.
# Table of Contents

Abstract ................................................................................................................................................iii

Acknowledgements ...............................................................................................................................iv

Dedication ...............................................................................................................................................v

Chapter 1: Introduction .......................................................................................................................... 1
   Problem Statement ............................................................................................................................ 1
   Research Questions and Thesis Statement ....................................................................................... 2
   Research Design ............................................................................................................................... 4
   Research Objectives ........................................................................................................................ 6

Chapter 2: Literature Review .................................................................................................................. 8
   Introduction to Change Management ............................................................................................... 8
      Strategy and Change ....................................................................................................................... 9
      Resources and Change .................................................................................................................. 10
      Hospitality Gaming and Change ................................................................................................. 11
   Relevant Topics in Change Management ......................................................................................... 13
      Conceptualizing Change .............................................................................................................. 14
      Social Resources as Competitive Advantage ......................................................................... 17
      Knowledge Management, Networks, and Structures ............................................................. 18
   Data-driven change ........................................................................................................................... 21
      Big Data Analytics ....................................................................................................................... 22
      Data and Decision Making ........................................................................................................... 24
      Social and Technological complexity ......................................................................................... 27
   Difficulty of Change .......................................................................................................................... 28
      Resistance .................................................................................................................................... 28
      Culture ......................................................................................................................................... 29
<table>
<thead>
<tr>
<th>Chapter Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge Transfer and Organizational Silos</td>
<td>31</td>
</tr>
<tr>
<td>Collaboration and Facilitation</td>
<td>32</td>
</tr>
<tr>
<td>Analytical Bonds (AB) and Analytic Facilitation (AF)</td>
<td>34</td>
</tr>
<tr>
<td>Chapter 3: Mixed Methods</td>
<td>37</td>
</tr>
<tr>
<td>Methods Background</td>
<td>37</td>
</tr>
<tr>
<td>Grounded Theory</td>
<td>38</td>
</tr>
<tr>
<td>Epistemological Assumptions</td>
<td>40</td>
</tr>
<tr>
<td>Embedded Research Design</td>
<td>43</td>
</tr>
<tr>
<td>Issues</td>
<td>43</td>
</tr>
<tr>
<td>Instrument Development and Validation Variant</td>
<td>45</td>
</tr>
<tr>
<td>Qualitative Strand</td>
<td>45</td>
</tr>
<tr>
<td>Quantitative Strand</td>
<td>46</td>
</tr>
<tr>
<td>Mixing</td>
<td>46</td>
</tr>
<tr>
<td>Hypothesis Testing</td>
<td>46</td>
</tr>
<tr>
<td>Data Collection and Institutional Review Board</td>
<td>47</td>
</tr>
<tr>
<td>Reflective Memos</td>
<td>48</td>
</tr>
<tr>
<td>Interview Data</td>
<td>49</td>
</tr>
<tr>
<td>Survey</td>
<td>50</td>
</tr>
<tr>
<td>Sample</td>
<td>51</td>
</tr>
<tr>
<td>Usage Statistics</td>
<td>52</td>
</tr>
<tr>
<td>Analysis Procedures</td>
<td>52</td>
</tr>
<tr>
<td>Qualitative Strand</td>
<td>52</td>
</tr>
<tr>
<td>Quantitative Strand</td>
<td>54</td>
</tr>
<tr>
<td>Merged Results and Analysis</td>
<td>55</td>
</tr>
<tr>
<td>Chapter 4: Analysis</td>
<td>56</td>
</tr>
<tr>
<td>Interview Data and Analysis</td>
<td>56</td>
</tr>
</tbody>
</table>
# Table of Contents

Open Coding: Effective versus Ineffective ................................................................. 57
  Analytic Function ........................................................................................................ 57
  Skills and Abilities ...................................................................................................... 59
  Outcomes .................................................................................................................... 61
Axial Coding: Unintended Deviation ............................................................................. 63
  Stakeholder and Situational Diversity ........................................................................ 65
  Need for Soft Skills .................................................................................................... 66
  Presence of Biases ..................................................................................................... 71
Selective Coding: Impetus for Deviation ....................................................................... 75
  Source of Deviation ................................................................................................... 79
  Reason for Deviation ................................................................................................. 82
  Emergent Theory ....................................................................................................... 84
Model of Unintended Deviation (MUD) ....................................................................... 85
  Survivalistic Overprotectionism ................................................................................ 87
Course Correction, Analytic Facilitation (AF), and Analytical Bonds (AB) .................... 89
  Embedded Quantitative Instrument ......................................................................... 91
Merged Results ........................................................................................................... 97

Chapter 5: Discussion .................................................................................................. 100
  Theoretical Implications ........................................................................................... 100
  Managerial Implications ............................................................................................ 104
    Hospitality Gaming .................................................................................................. 107
    Network and Organizational .................................................................................... 110
  Limitations ................................................................................................................ 111
Future Research ......................................................................................................... 114
Conclusion .................................................................................................................. 116

Appendix A: In-Person Survey Questions ................................................................. 119
List of Tables

1 Exploratory factor analysis of overall survey (n=47) ................................................................. 94
2 Exploratory factor analysis of AF and knowledge sharing (n=24) ...................................................... 96
3 Regression summary for predicting AF .................................................................................................... 97

List of Figures

1 Analytical bonds and analytic facilitation .................................................................................................. 5
2 Embedded mixed methods design ............................................................................................................. 44
3 Emergent theory after open and selective coding ..................................................................................... 76
4 Model of unintended deviation (MUD) ..................................................................................................... 86
CHAPTER 1

Introduction

The diversified hospitality business model has unique challenges. Because there are several business types working in unison, a multitude of organizational behavioral issues are bound to arise. Understanding the role of data analytics within these issues is important, given that data plays an integral role in the business world today. To be data-driven is a way of saying that firms make business decisions based on empirical evidence rather than intuition. It has been established that being data-driven is highly desired by firms, both in hospitality gaming and beyond (Barton & Court, 2012, Bean, 2017, McAfee & Brynjolfsson, 2012).

With such a wide range of businesses in today’s diversified global hospitality and gaming corporations, firms have a bevy of systems to navigate. This list can include proprietary and third-party systems designed around the operations of hotel, casino, slot machines, slot systems, table games ratings, player kiosks, casino player management, player development, point of sale, revenue management, in addition to finance and accounting systems. Casinos, hotels, and restaurants can be considered businesses unto themselves and syncing the requisite systems between them is no simple feat.

Problem Statement

Despite the yearning for a data-driven business culture, less than 28% of firms in a survey of Fortune 1000 executives claimed to have actually established data-driven change and seen value from their data-driven programs. The remainder felt as if they have started and not seen value, or not started at all (Bean, 2017, April). As businesses scale up, the need for data-driven solutions have become inevitable since improving incremental performance can have tremendous upside over the long run. Many barriers remain in achieving cultural adoption, as the technologies for many managers may be too exotic. In the pursuit of data-driven change, the cultural challenges have been reported to be challenging (McAfee & Brynjolfsson, 2012).
Data-driven change may have unique challenges, but change in a more general sense is also considered difficult as 70% of change efforts have been reported to fail (Balogun & Hailey, 2008). Although the dawn of the information age came with great promise, experts have claimed that Big Data has failed to deliver and is being underutilized (Bean, 2018, April 25; Easterbook, 2018, April 22; Tenner, 2018). University of Nevada Las Vegas professor Anthony Lucas has remarked about hospitality gaming firms saying that, “the challenge of Big Data is actually affecting change...it’s political, uncomfortable, and difficult, to take on that existing operating theory” (Rothberg, 2017, para. 23). Despite the rapid emergence and advanced capabilities of data technologies, adoption in hospitality gaming has been an ongoing challenge.

Research Questions and Thesis Statement

Considering the unique challenges associated with data-driven change, the research questions focuses on the following:

1. Why is data-driven change in hospitality gaming difficult?

2. How can theory better inform the problem?

These questions explore more deeply the difficulty of data-driven change, taking into consideration the unique aspects of hospitality gaming. This exploration is performed, with the assumption that data-driven decision making powered by Big Data is the ideal, and that some phenomenon is preventing this ideal from materializing. In describing this ideal in more detail, Big Data analytics is regarded as a requisite to and synonymous with business intelligence. Originally, the term ‘Big Data’ began appearing in the mid 1990s and became ubiquitous by 2012 (Diebold, 2012). Many years later, it remains an ideal; a destination seldom reached (Bean, 2017, April). Bean (2017, April) summarized that the biggest obstacles to data-driven change are due to cultural and resistance factors. Within gaming-hospitality, Rothberg (2017, June 26) found that cultural divides between the front and back of house made adoption challenging; managers were resistant to adopting new forms of reporting and preferred to stick to classical views of the
operation. Although the terms ‘Big Data’ and ‘data-driven’ may quickly be classified as a technical matter, the challenges of managing it have appeared to be more a matter of organizational behavior. Therefore, the thesis of this dissertation is that through qualitative exploration, stronger theory can arise in explaining the difficulties of data-driven change.

This dissertation makes the claim that current explanations for why data-driven change is difficult have done little to describe the root cause of the problem. Cultural and resistance factors are generically identified symptoms of a deeper diagnosis. Furthermore, collaboration, knowledge sharing, and facilitation are concepts that may address the issue but have done little to drive widespread adoption—the problem warrants greater theoretical investigation.

In addressing the research questions, this dissertation advances the model of unintended deviation (MUD). This theory shows that subsequent to top management buying into data-driven change, network actors will exhibit survivalistic overprotectionism. Specifically, decisions related to departmentalization and resource allocation cause managers to use analytic resources to advance biased narratives that may fit their self-interest but present a facade to top managers that business results are analytically informed. The theory implies that this deviation away from objective data-driven decisions and towards subjectivity is unintended. This is because the ideals of data-driven change—in that data are driving decisions, and not intuition—is an accessible and easy concept to believe in. However, the current study shows some preliminary evidence that the mere belief in data-driven change is distinct from the desire to become involved in it. Involvement in this context relates to analytic facilitation (AF).

While the MUD provides an explanation for the difficulty of data-driven change at the macroscopic level, AF clarifies the problem at the interaction level. AF activities and behaviors are essential to the development of analytical bonds, which refers to a specific kind of network interaction not previously identified in research. This interaction occurs between a sender and receiver of an analytic deliverable (Figure 1). Oftentimes, this involves decision making leaders and others that are tasked to perform analytics but whom themselves cannot enact those decisions. Because analytic teams inform decisions throughout an organization, these kinds of interactions
may be less formal in nature and would be unseen by way of the traditional organizational chart; a point underscored by Hollenbeck and Jamieson (2015).

In examining this research problem, research lenses were drawn from the social, organizational, and management sciences and applied to the research problem. While this is a mixed methods study, the primary research approach was qualitative and applied grounded theory, which is considered appropriate for studying interpersonal relations and their connections to broader social processes (Charmaz & Belgrave, 2007). The research design also included an embedded quantitative instrument, whereby the researcher combined the collection and analysis of both quantitative and qualitative data within a traditional design (Creswell & Clark, 2007).

**Research Design**

The qualitative study was the priority research stream; the quantitative stream played a secondary role and was embedded within the broader qualitative design. The qualitative grounded theory design included compiling and analysis of qualitative data that consisted of reflective notes, interview data, and also literature. Interview data was collected from twenty-five subjects, all of whom had at least five years of management experience in hospitality gaming. They were asked questions on analytics and the dynamics related to data-driven change. Also, hundreds of reflective notes were collected over an eight year span by the researcher. The interviews, literature, and the reflective memos were triangulated to enable the grounding of the developed theory (Locke, 2001).

Ultimately, this dissertation was a qualitative study on the difficulties of Big Data analytics. The embedded quantitative instrument was conducted at the pilot study scale. This did produce significant findings, which even though exploratory in nature, the ability to apply scales and measurement is considered welcome into the change management field. Todnem (2005) discussed that the research area has been lacking in valid frameworks. The quantitative data consisted of usage statistics and a survey instrument performed on employees at a casino. This included a survey that was administered to frontline service employees. They were each asked to complete a 20 question Likert-style survey that attempted to measure behaviors and attitudes that informed
Figure 1. Analytical bonds and analytic facilitation.
the concept of AF. Their responses were matched with usage data provided by their employer. The survey results underwent factor and regression analyses to see if there was a relationship between report usage and other data-driven change concepts informed from the survey.

**Research Objectives**

The research methodology of grounded theory was applied to fit the research questions. The purpose of this was to develop new theory that provided a general explanation of a process (Creswell, 2015), in this case data-driven change. What resulted was the Model of Unintended Deviation (MUD). The theory established survivalistic overprotectionism as the impetus for deviation. Analytic facilitation (AF) was also described, which is an interaction specific to data-driven change and plays a critical aspect to the formation of ABs. The new theory predicted that when survivalistic overprotectionism goes unchecked, deviation away from ideal data-driven change worsens; as deviation increases, the MUD predicts that strong analytical bonds become fewer and are harder to develop.

Together, the MUD, AF and AB improves the existing toolkit for assessing the difficulties of data-driven change and considers the network and behavioral factors unique to hospitality gaming. By applying the MUD framework to the hospitality gaming organization, leadership can gain a stronger understanding of the root causes of why data-driven change is difficult. The reason it is so difficult is because it can easily go unrecognized or unnoticed. The MUD can affect change by calling attention to the unobserved overprotectionism that results from otherwise well-intended investments and organizational structure decisions. This unintended deviation occurs as unnecessary competition arises from the creation of departmental silos. While it has been recognized that silos can hinder the knowledge transfer process (Tett, 2015), the MUD brings attention to how investing in analytics can have a reverse effect on an intended trajectory towards objective data-driven decision-making. The overprotectionism that arises from silos and competition can cause stakeholders to use the vast amounts of data that is available to them in a way that increases bias.
The qualitative data also highlights that the hospitality gaming industry is prone to unintended deviation. This is not just because distinguishing overprotectionism from general protectionism is challenging, but also because the day-to-day demands of the hospitality gaming industry make the transfer and translation of Big Data analytics all the more difficult. The ability to recognize unintended deviation sooner can help drive data-driven change more efficiently and prevent future underutilization of analytic resources.

AF are defined in this study as a set of behaviors and activities unique to data driven change. It is claimed to be critical to both prevention and course correction from deviation. A pilot study provided indications that report usage is a viable approach to developing a scale for measuring analytic facilitation at the employee level. Signals that deviation is about to occur may be difficult to spot and is especially true when looking solely through the lens of the organizational chart. Traditional hierarchical views of the organization while useful for determining formal decision-making power, is less relevant in a data-driven network. If the ideal is to have Big Data analytics drive strategic decisions, no longer is the formal decision making power dictated by the lines that indicate the rank of the individual; the lines also to be considered are analytical bonds (AB).

Only visible through a social network lens, these bonds operate independently of formal rank. The strength of these bonds are a function of the network actors AF values. ABs are characterized by a linkage of employees with significant AF values, whether they are analysts or not, to get actively involved in the data-driven change process. This is reflective in their attitudes towards training and understanding the process of changing the intelligence they get to perform their jobs. Usage statistics show a potential glimpse into measuring AF and AB throughout a network. Though raw usage scores say little about how users are using reporting solutions, and only show how much they are using them, defining effective usage should be important to any firm making key strategic investments in Big Data analytics.
CHAPTER 2

Literature Review

The objective of the literature review is to familiarize the reader with the topics relevant to the theory advanced in the dissertation; beginning with the broadest areas and narrowing towards the more specialized topics. The literature review concludes with the introduction of analytical bonds (AB) and analytic facilitation (AF)—new concepts that inform the unique aspects of data-driven change at the level of interaction and involvement. While change has been generally conceptualized at the macro-organizational level, the argument is made throughout this chapter that because of the social complexity involved in change, new theories on data-driven change must acknowledge interaction level dynamics. Moreover, these intricacies are not necessarily visible to managers via traditional means, most notably through an organizational chart.

The literature review contains five sections. The first two sections were written to familiarize the reader with the field of change management: the general research area as well as selected topics relevant to the current study. These first two sections include an introduction to the broader area of change management, historical and contemporary perspectives on change, as well as relevant topics in management and hospitality. As the scope narrows, case studies and criticisms of the field are provided as well as an overview of the complex issues that arise in the change field both in hospitality and management studies as a whole. The third section looks at the specific issues related to data-driven change focusing on the technological and managerial challenges involved. The fourth section addresses the extant literature on the difficulty of change with respect to both identified culprits of difficulty and commonly cited remedies. This final section also summarizes the gap in the literature on the difficulty of data-driven change making the claim that resistance and cultural factors have only come so far in describing the problem. Applying a network framework and introducing the constructs of AF and AB, this final section considers the important characteristics of data-driven change germane to the methodological considerations applied in Chapter 3.
Introduction to Change Management

Change has been viewed along two major paradigms (Robbins & Judge, 2013). The first paradigm addressed change as an occasional process to a system that otherwise maintains a certain status quo. This approach is rooted in Lewin (1958) that proposed a three-step model of change whereby an organization unfreezes, then changes, then refreezes to a new sustainable equilibrium state. This approach was noted to reflect a different business era where organizations were more rigid and favorable to routine operational processes. These organizations were taller and more hierarchical than the flatter organizations that are a more recent phenomenon.

The other more contemporary paradigm looks at change as a more continuous process whereby change is constantly occurring. This approach brings into play the concept of a dynamic organizational structure—in other words a more organic model and less so a mechanistic model (Robbins & Judge, 2013). Change management has been defined as, “the process of continually renewing an organization’s direction, structure, and capabilities to serve the ever-changing needs of external and internal customers” (Moran and Brightman, 2000, para. 1).

One leading framework for change was outlined in Kotter (1996), where a distinction was drawn between change leadership and change management. Kotter pioneered an eight-step model on the change process. The steps were established as follows: (a) establishing a sense of urgency, (b) forming a powerful guiding coalition, (c) creating a vision, (d) communicating the vision, (e) empowering others to act on the vision, (f) planning for and creating short-term wins, (g) consolidating improvements and producing still more change, (h) institutionalizing new approaches. At the end of this process, the change process is said to return back to the first step of looking for a new urgency. Like the more contemporary views of change, Kotter went further to imply that change is not just continuous, but also that the desire to change should be constant. The concept of change has evolved from a time when change was deemed as a much more rigid process whereby today, change appears to be a fluid and necessary part of strategy.
**Strategy and Change**

Why do businesses have to change? Strategy was described as performing activities differently than competitors. Michael Porter, a professor at Harvard Business School, stated that it is not enough for a company to perform at a high level simply through operational effectiveness. It has been established that a company must also have features that make it different from its competitors (Porter, 1996). According to Porter (2008), businesses have to respond to five market forces that affect the firm’s strategic positioning in relation to the competition. Those forces were described as: (a) the threat of new entrants, (b) the threat of substitutes, (c) the bargaining power of customers, (d) and the bargaining power of suppliers. It became clear that remaining competitive over the long run required firms to change. In the view of Porter (1996), the most effective firms take on activities that minimize the inefficiencies that arise from shifts in activities or what he called trade-offs (Porter, 1996). Selecting the right kinds of activities also included the combining of activities to existing core competencies in a complementary fashion; or what he called fit (Porter, 1996). The author claimed that economic gains are produced when adding new activities in a way that the very ability to add activities is a core competency itself. This suggested that a firm’s strategic advantage is more sustainable over the long run because it is more challenging for a rival to imitate an array of interlocked activities than it is to simply replicate the standalone activities (Porter, 1996). Essentially, the competition can always look at what new activities the competition is doing but are not privy to how those activities are being accomplished. Adding to the argument, Porter established that businesses are constrained in how much change they can manage. Available resources for enacting change initiatives are not bottomless. This point reinforced the notion that if analytics are to play the role of strategic differentiator for hospitality gaming firms, than those resources should be managed effectively with respect to the activities that are performed.
Resources and Change

To the last point of resources, Daft (2012) defined a firm’s resources as the resources that include all assets, capabilities, processes, information, and knowledge that is under the firm’s control. These resources can be enabled to implement strategies and improve efficiency and effectiveness. Barney (1991) discussed how the availability and imitability of the processes and input resources determine the sustainability of competitive advantages. In other words, the easier it was for a competitor to mimic the innovations of a competing firm, the shorter the competitive advantage would last. Sustainable business models and some routine was found to be important, but the contemporary view of change was determined to be one where competition requires continuous agility to move through a competitive landscape.

Barney (1991) also identified that resources related to competitive advantage can be evaluated based on their value, rareness, imitability, and substitutability. It was argued that competing firms cannot have identical resources because if that were true, then first mover advantages would not be possible (Barney, 1991). The heterogeneity of resources across and within firms provide the basis for which firms can optimize and create sustained competitive advantages (Barney, 1991). This view was relevant because it shed light on the difficult problem of managing a diverse range of resources efficiently, and most notably, the multi-business arena of hospitality gaming.

Hospitality Gaming and Change

One of the more important changes that the hospitality gaming space is continuously experiencing is diversification. This what are globally referred to as integrated resorts—firms have had to manage a greater array of hospitality products and services. Conceptually speaking, this has been termed related-corporate diversification whereby businesses expand their product mix into streams related to their existing offerings (Hesterly, 2010). The suggestion has been made that this phenomenon also creates more diversity in the competitive landscape, which enables firms to compete across different categories (Karnani & Wernerfelt, 1985).
Okumus and Hemmington (1998) found that viewing change as a continuous process is more relevant, and that Lewin’s theory on change as a freeze and refreeze process was less relevant in modern business. From a study that used interview data across 25 hotels, it was found that managers rarely seek to refreeze newly adopted processes and that most seek to follow up with further changes (Okumus & Hemmington, 1998). Kale (2005) found that because the hospitality business is heavily dependent on being responsive to customer relationship management or CRM and database marketing needs, having an organizational structure that is sufficiently dynamic to respond to changes is imperative to business optimization. The literature on change in hospitality and gaming have agreed with the view of Robbins and Judge (2013) that stability and predictability are concepts that are becoming less relevant in today’s business world.

The fluidity of change in the hospitality gaming sector is not simply about strategic moves in relation to the competition. It has also been dictated by change occurring in the broader landscape of business and society as a whole. The five forces model of Porter (2008) has been relevant to the competitive landscape as it changed in response to gaming’s regulatory history. In turn, these changes had an effect on how gaming firms strategically positioned themselves. To this point, Bernhard, Green, and Lucas (2008) described the contributing factors to the historical shifts in management culture that occurred in gaming. Las Vegas was not always a town of large mega-resorts and instead, in its origins was run by figures more associated with the Wild West. This era was followed by the industry being run by leadership that was well connected to organized crime. However, it has been suggested that this was society’s own doing that all started with Prohibition. By banning alcohol, this played into the hands of enterprising immigrants that were looking to capitalize. The creation of black markets enabled organized crime to proliferate and wield tremendous influence in American society. Through the decades, and with watershed moments such as the Kefauver Hearings, law enforcement have become more effective and the mob’s influence waned. This gave rise to legitimate business organizations, embraced by Wall Street, taking over and shaping Las Vegas into the global city it is today (Bernhard et al., 2008).

The globalization of the Las Vegas model is a good example showing that new markets have
had to manage broad change with respect to the introduction of legal gaming and the respective social and economic impacts to host communities (Eadington, 1999). Contributions such as Eadington (1974) and Shoemaker and Zemke (2005) helped to bring understanding around the differences between local and destination casino markets as well as rural and urban ones.

Classification of casino assets and categories has proven and still continues to be difficult (Cser & Ohuchi, 2008). This complexity and diversity within the history of casino development exposes the possibility that achieving change may involve different variables depending on the situation.

**Relevant Topics in Change Management**

To this point in the chapter, change has been described with respect to the dominant paradigms of intended change. It has been established that firms do need to change in response to competitive and environmental forces. While the need for change is continuous, it does not follow that change always implies desirable outcomes. Scholars of change management should also be familiar with some of the prominently cited case studies.

In the 1980s, Jack Welch, CEO of GE pioneered business practices that included implementation of six sigma and 360-degree feedback (Harry, 1998). From the similar period, Japanese automaker Toyota achieved huge advances in production efficiency by developing Just in Time and Kanban manufacturing processes (Sugimori, Kusunoki, Cho, & Uchikawa, 1977). This fostered their growth into a market leader and transformed the entire industry through the reinvention of the traditional assembly line.

During the Enron scandal, a corporate culture of pumping up the stock price became pervasive. With no limits on how artificial the stock value was, high-level executives allowed the firm to topple with the sole interest of preserving their own wealth, even at the cost of dissolving the value of shares held by lower-level stockholders that were not privy to the creative accounting that was taking place (Li, 2010). Situations such as this one highlight that not all change is for the better. Also, this example does show that change affects different parts of an organization in different ways. Executives Jeff Skilling, Andrew Fastow, and Kenneth Lay were part of a subnetwork within Enron and had access to clandestine information, which allowed the stock
price pumping culture to spread through the organization. Unfortunately in this case, demonstrating real value added was not part of the broader change effort.

These two historically prominent case studies were just the tip of iceberg, and more have occurred since then. The lasting impacts of both of these cases echoed the sentiment that understanding change has never been greater than in the current business climate (Todnem, 2005). Data-driven change in hospitality gaming, which lies at the heart of this dissertation, has had less than desirable outcomes (Rothberg, 2017, June 26). Despite consensus among scholars on the urgency of understanding change, the concept of change is still considered to be a difficult concept to pin down.

**Conceptualizing Change**

Todnem (2005) addressed the lack of consensus among academics and practitioners on how to define change management. The purpose of Todnem (2005, pp. 369) was “to provide a critical review of theories and approaches currently available in a bid to encourage further research into the nature of organizational change with the aim of constructing a new and pragmatic framework for the management of it.” This was useful to the current study because it shed light on the contradictory nature of change in that it is readily understood, but remains difficult to conceptualize. Todnem categorized the conceptualizations of change in the following ways.

**Change as a rate of occurrence.** In line with historical perspectives on change, Todnem (2005) expressed that change can be thought of either as a continuous or discontinuous process. Other authors have even characterized this dynamic as ‘smooth’ or ‘bumpy’ change (Grundy, 1994). Smooth change was referred to as changes that are made in a systematic and predictable way at a constant rate, whereas bumpy change was described as more sporadic changes occurring with periods of relative quiet followed by accelerated change initiatives (Grundy, 1994).

**Scale of the change.** Dunphy and Stace (1993) identified that change can come in different sizes: fine-tuning, incremental adjustment, modular transformation, and corporate transformation. Fine tuning was described as an ongoing process that implements change that are respective to the current strategy. According to Senior and Fleming (2006), incremental
adjustment involved strategic management thinking but fall short of radical change. Modular changes can be applied to hospitality gaming and is described as shifts happening to one or several departments or divisions inside a company (Todnem, 2005). For example, a change to a casino strategy may include other adjacent parts such as food and beverage (i.e. casino bar).

**How change comes about.** Another key distinction was how change arises as it may be considered a planned or emergent change (Todnem, 2005). The literature on planned change tried to explain the process leading up to an eventual change. This approach addressed the different stages in which an organization goes through starting from an undesired state to a desired one (Elrod & Tippett, 2002). This was not unlike Lewin (1958) whereby an organization unfroze then refroze. However, as echoed by Robbins and Judge (2013), this planned approach has become outdated by critics in favor of the emergent approach to change.

The key distinction made between planned and emergent approaches was that planned approaches were considered to originate from the top of an organization whereas emergent change efforts are considered to occur in more of a bottom-up way (Bamford & Forrester, 2003). Emergent change was much more widely accepted and considered more relevant to today’s organizations due to the constant need to adapt to market forces (Todnem, 2005). As a result, this approach placed an emphasis on gaining a deep understanding of strategy, structures, and systems in addition to social factors that cause organizations to either promote or resist change (Burnes, 1996).

By discussing social factors and emergent change as being unplanned, Todnem (2005) overlooked what should be considered an important point about change as a social network phenomenon. Within this network framework, change is conceptualized as a process of diffusion. The illustration of an epidemic is a common example of diffusion with some people become infected while others do not depend on their exposure levels and their susceptibility. Also popular in marketing, terms such as ‘viral’ are expressed as a means for understanding how certain trends spread across customers. If this sounds familiar, the concept of social contagion was brought to the mainstream through Malcolm Gladwell’s *The Tipping Point* (Gladwell, 2006). The basic
concept being that any trend that catches fire per se, originates with a group of early adopters, followed by an early majority, followed by the late majority, followed then by the laggards. The contagion is transmitted faster through some individuals based on their exposure to other individuals, much like a virus. The network structure of one population may cause a contagion to spread more quickly than a similarly sized network that has a different structure. The interactions that cause diffusive change occur at the interaction level is precisely what the concept of analytical bonds (AB) addresses. At the end of this chapter, it is posited that data-driven change requires a specific kind of interaction that requires those with formal power to entrust some of that power to those that perform analytics that inform those decisions but cannot enact those decisions.

In a related vein, to the point that planned change originates from the top (Bamford & Forrester, 2003), in the network framework, this relates to the concept of decision centrality. Within a traditional organizational chart, big decisions start at the top and smaller decisions do not require upper management approval. By contrast, in an emergent view of change where change occurs through various parts of the organization, the decision is separate from the influence that affected those decisions. Whereas Todnem (2005) provided ample evidence that change can be conceptualized in different ways, the views from Bamford and Forrester (2003) and Gladwell (2006) gave convincing arguments that any broad change inevitably required social processes occurring throughout an organization and not just buy-in at the very top. This point became important to the theory advanced in the current study in that top managers—despite their best intentions—may be blind to some of the adverse impacts of their own decisions.

In summarizing how change has been addressed phenomenologically, there was little doubt that change is complex and difficult to conceptualize, let alone measure. Bergh and Fairbank (2002) discussed that change remains a very complex thing to measure despite the recognition on a more general scale that it is a distinguishable phenomenon. Statistical reliability issues must be given careful consideration before determining findings to be significant and generalizable. A content analysis of 126 change studies was performed that determined that strategy researchers tended not to follow statistical requirements that were sufficiently stringent (Bergh & Fairbank,
Only 6 of 126 studies addressed reliability and 4 of 126 controlled for violations of assumptions in statistical procedures. These figures showed that applying measurement to a social process might be challenging. This gap in the research was also an opportunity for the current study to fill. Firms would benefit from the ability to quantify and track their change efforts; doing so would represent a competitive advantage.

**Social Resources as Competitive Advantage**

Can the ability to change with respect to social processes be a competitive advantage? According to Barney (1991), if competing firms had homogenous resources, then barriers to entry could not be exploited as one firm could easily develop or acquire a competing firm’s change in strategy. Therefore, it is the heterogeneity of resources across firms as well as the immobility of firms that leads to the concept of sustained competitive advantage (Barney, 1991). One of the key reasons for a firm’s resources may be imperfectly imitable is due to social complexity (Barney, 1991)—the answer to the question at the beginning of this paragraph is then ‘yes’. There may be certain social behaviors and phenomena that go beyond the ability of a firm to manage and influence its workforce (Barney, 1991). This underscores the argument that the ability to change inevitably requires social processes throughout the organization and not just top-management buy-in.

Barney (1991) identified four attributes of strategic resources that can lead to sustained competitive advantage: (a) It must be valuable in that it exploits or neutralizes threats; (b) It must be rare among competitors in the current environment; (c) It must be imperfectly imitable, meaning it is not easily attainable by competitors; (d) It cannot be easily substitutable by something strategically equivalent.

Barney (1991) argued that one source of inimitable resources comes from the nature of interpersonal relations and an organization’s culture. These attributes may not easily be duplicated by competing firms because the people resources are not identical. He noted that organizational research such as organizational behavior and organization theory, could be a rich
source of information for helping to identify rare, non-imitable, and non-substitutable resources. In this sense, the ability for a firm to communicate and facilitate effectively on data-driven concepts is potentially a competitive advantage.

Nahapiet and Ghoshal (1998) made a similar argument to Barney (1991). The researchers stated that an organizational advantage arises from the combination of social and intellectual capital. Through the processes of social exchange and the combining of activities, intellectual capital is formed. By doing so effectively, firms can gain a competitive advantage. It is not just the activation of the skills in the workforce, but also, the structure of the network that maximizes the opportunities for combination and exchange to occur.

Nahapiet and Ghoshal (1998) also discussed that through combination and exchange, new interpretations—or ‘change’ for that matter—arise through the development of new shared languages, codes, and narratives. If it is to be accepted that social complexity and interpersonal communications can be a source of sustained competitive advantage (Barney, 1991; Nahapiet & Ghoshal, 1998), then the issue of knowledge management becomes important. In a data-driven world, it seemed that the difficulty of data-driven change was not for lack of having information. The intellectual capital in a data-driven context seemed to require a social competency to become effectively leveraged. Analytical facilitation and analytical bonds it would seem could help to fill this gap in the literature.

**Knowledge Management, Networks, and Structures**

Knowledge management has been defined as a process of organizing and distributing collective organizational wisdom in a manner that is both timely and targeted with respect to the recipients of the information (Robbins & Judge, 2013). Knowledge management is described to include the strategies and processes of identifying, creating, capturing, organizing, transferring, and leveraging knowledge to help individuals and firms complete (O’Dell, Grayson, & Essaides, 1998). Knowledge management is also described to include the specialized technical knowledge held by both individuals and the firm (Brown, DeHayes, Hoffer, Martin, & Perkins, 2008).
While it is true that knowledge management can be leveraged in value added ways, it does not necessarily follow that this is performed responsibly. Irresponsible practices were evident in the Enron scandal where executives withheld critical knowledge for personal gains to themselves, all while delivering a false narrative to company stakeholders and employees that would ultimately be slighted by the misinformation. Knowledge management is therefore a critical piece of the change process—a process that is also inherently complex socially.

Examples of exclusive subnetworks networks echo the point that the arrangement of smaller group networks is important to the way business decisions are made. Different arrangements may produce different results depending on their structure. This brings into the fray, the contingency based approach to organizational design, which takes into account environmental factors and recognizes that the ideal structure may not be static across all settings (Pennings, 1998). Contingency theory has been validated and included in most modern organizational textbooks (Pennings, 1998). To both the point that shared languages, codes, and narratives are important to change (Nahapiet & Ghoshal, 1998), and with respect to contingency theory (Pennings, 1998), the concept of subnetworks adds another consideration to the management of change. This becomes important with respect to the theory advanced in this dissertation in that creating subnetworks via departmentalization may create unintended issues despite the intention to develop functional areas in an organization.

Knowledge management and network concepts have been discussed as key to understanding the way that information and resources flow through different networks is not uniform (Scott & Carrington, 2011). With respect to social network analysis, there may be information bottlenecks in organizations that are vital to the spread of information (De Nooy, Mrvar, & Batagelj, 2011), and computer models have shown that diffusion occurs more slowly in networks with a few highly connected nodes compared to more random networks (Gibson, 2005). The amount of ties in a network is known as network density, and is one of several concepts in social network analysis that relate to achieving network wide diffusion; also known as 100% adoption. Exposure relates to the proportion of neighboring nodes that have adopted a change at a
certain point in time. Exposure relates to the required proportion of neighboring nodes for an individual node to adopt a change (De Nooy et al., 2011).

It follows that early adopters of change will generally have lower thresholds and late adopters have higher thresholds. If there are too many people with high threshold in the beginning of a change effort, achieving critical mass may be challenging. Critical mass is defined as the minimum number of adopters needed to sustain a diffusion process (De Nooy et al., 2011).

Networks can also change in size adding another layer to the diffusion picture. This depends on the role of network bridges, a special kind of relational tie that links together network components, which can be thought of as previously unconnected islands of subnetworks. These social network concepts introduce a new framework for understanding change as social process. This is a corollary to the understanding of change as a more top-down management concept. The argument here is that both viewpoints are necessary.

By pointing out the aforementioned social network concepts, what was being called into question here is the value of the traditional organizational chart. These root structure looking diagrams are said to represent a division of labor that “must be carried out through non-overlapping functional divisions, with a hierarchy of coordination and control and with procedures and rules of action that guarantee formalized and impersonal relationships among its members” (Molina, 2001, pp. 79). Originally, the creation of these charts reflected a rational approach to dividing labor into bureaucratically separate units (Molina, 2001). However, several scholars have noted the shortcomings of the ‘org chart’ in conveying the intricacies of network dynamics. Rummler and Brache (2012) noted that what was lacking from traditional organizational charts were the customers, products and services provided, as well as cross-functional workflow that occured across the organization. Furthermore, traditional organizational charts have been claimed to fail in providing a sense of information spreading across a firm in more informal ways, which is more true to how social networks behave (Hollenbeck & Jamieson, 2015). As organizations grew, evolved, and became more complex in relation to changing environments and technologies, the traditional organizational chart has been
claimed to become more of a liability (Rummler & Brache, 2012). One such technological change was the advent of Big Data analytics.

Data-driven change

It has been argued up to this point that change requires an understanding of the social aspects of the process. While some scholars claim that new knowledge can be shared to create a source of competitive organizational advantage, it does not change the fact that specialized knowledge at the subnetwork level can be managed ineffectively, or even worse, irresponsibly. Traditional organizational charts are limited in their ability to address complex social network dynamics. While these considerations are important to change as a broader topic, data-driven change warrants special attention. Before diving in to the nuances it is important to first have a base understanding of Big Data analytics.

Robbins and Judge (2013) cited technology as being one of the main forces of change. With respect to the importance of resource management Barney (1991), data can be considered an important resource in a competitive business environment. Barney (1991) recognized the potential role of information technology in creating sustained competitive advantage. Certain firms may be able to exploit technology better than others, even if these firms possess the same technology (Barney, 1991). The acquisition of computer hardware by itself is imitable, but if these technologies are used to inform strategic decisions in unique ways, the technology combined with the adoption of it then becomes more inimitable (Barney, 1991). Therefore, between two firms that have identical technology, the firm that is able to exploit their technology resources more effectively will operate more efficiently.

To this point, the question was raised of how best to exploit data technologies? To address this question, it is important to confront the nature of data itself. Ackoff (1989) originated the concept of the knowledge pyramid or DIKW, which stand for data, information, knowledge, and wisdom. This concept helped to explain that data in of itself are bits and bytes existing on servers and disks. It is the manipulation and interpretation of that data that makes it informational. Today, more data is collected than at any other point in history. However, it remains no secret that simply
having more data does not make the challenges of data-driven change any easier.

**Big Data Analytics**

Big data has become a more prominent phenomenon in the last decade as the technology continues to develop. Despite the ubiquity of Big Data, the term is not firmly rooted in strong definition (De Mauro, Greco, & Grimaldi, 2015). By performing a survey of existing research, De Mauro et al. (2015, pp. 103) concluded that “Big Data represents the information assets characterized by such a high volume, velocity and variety to require specific technology and analytical methods for its transformation into value.” Terms such as high volume and big should also be put into context. McAfee and Brynjolfsson (2012) cited that in 2012, about 2.5 exabytes of data are created every day and this volume is doubled every 40 months. Also, more data flows through internet every second than what was stored on the entire Internet but twenty years prior. IBM projects that there are 2.5 quintillion bytes of data generated every day (Baesens, 2014). Data resources have also become cheaper and storing more of it has not been a problem (Ayres, 2007). While the possibilities of collecting vast amounts of data with relative ease may seem exciting, the challenge of managing information has not received as much attention.

To this last point, database management is an area of expertise within the information sciences. The emergence relational databases gave rise to the need for managing different types of data. Especially in a diverse business like gaming where there are a myriad of source systems, all of that data does not magically clean itself. All of that data must be processed, sorted, and loaded into a data warehouse. Brown et al. (2008) defined the data warehouse as the establishment and maintenance of a large data facility containing data on many, if not all aspects of the broader enterprise. In hospitality and gaming the broader enterprise is a highly diversified entertainment product.

There are some enterprise resource planning (ERP) systems designed by companies like SAS, which may provide opportunities for integration, but technological challenges still exist. For example, in a 24-hour industry, when should things get booked to accounting at the individual
day level? Should it be right at midnight or more respective to a late night on the town? Also, database administrators must assure that correct data types (e.g. string, character, text, numeric, decimal) are properly setup to extract, transform, and load (ETL) into the data warehouse. Data security is another concern as the personal data collected can be very sensitive information. For example, Las Vegas Sands’ database was hacked in February of 2014 (Stutz, 2004, February 11). Recognizing how long to store data also becomes an issue. Despite the availability to vast amounts of data and the desire to utilize it, hospitality’s relationship with Big Data analytic solutions is still not well developed (Xiang, Schwartz, Gerdes Jr, & Uysal, 2015).

Some would contend this last point. Loveman (2003) would suggest that the gaming industry was a pioneer in the usage of Big Data as his company in particular (Caesar’s Entertainment), was one of the first firms to adopt CRM. This point aligned with the view of Piccoli, Connor, Capaccioli, and Alvarez (2003) whom noted that the hospitality industry was an opportune place for capitalizing on CRM-based strategies because of the high degree of interaction with customers. CRM posits that the objective of marketing should not simply be to have the broadest visibility among the masses, but to segment customers based on their lifetime value to the firm, and correspondingly, allocate more marketing spend to the higher valuable customers. Much of the segmentation that occurs today is based on the concepts of RFM or recency, frequency, and monetary value introduced by Bauer (1988).

Even though hospitality gaming has been a pioneer in leveraging Big Data, experts would agree that there remains room for improvement in developing data analytic solutions. For example, assigning monetary value to a customer in an industry where the customer can actually win money from the casino is not a straightforward exercise. In other industries, like subscription-based models, applying simple financial discounting formulas may be applicable (Berger & Nasr, 1998). The gaming industry accounts for volatility by working with both theoretical and actual win values (Lucas & Kilby, 2012). Still, the concept of loyalty is also not always straightforward. Aside from having strong or weak loyalty, latent or spurious loyalty (Tanford & Baloglu, 2013), customer lifetime value estimation is continuously challenging as
companies continue to refine their predictive capabilities. Improving segmentation accuracy would prevent misclassification of customers, which could, for example, result in a high value customer not receiving the kind of reinvestment that they deserve (Malthouse & Blattberg, 2005).

Another opportunity for value added analytics lies in the popularity of social media. eWOM or electronic word of mouth marketing is becoming more relevant with today’s consumer with sites such as Yelp! and Trip Advisor (Cantallops & Salvi, 2014). Noone, McGuire, and Rohlfs (2011) noted that hospitality and gaming firms stand to benefit tremendously from leveraging information about their customers through social media. This includes, but very much not limited to, using social media as a marketing distribution channel, for targeted marketing, as a tool for social engagement, and to identify key brand ambassadors. These kinds of activities will require analysts to translate simple marketing premises into informed methods for mining and disseminating findings from Big Data. Still a young field, this kind of analysis would not have otherwise been possible just a couple decades ago. For example, a sentiment analysis could be performed on Twitter comments that post a specific hashtag. Today’s statistical packages are able to perform text analytics that incorporate natural language processing. By setting rules around a language corpus, an analysis could provide insights that go far beyond garden variety metrics including impressions, tweets, and retweets. Philander and Zhong (2016) utilized a dictionary based sentiment analysis approach to develop sentiment scores and ranks across various integrated resorts in Las Vegas. Philander and Zhong (2016) also performed validity and reliability checks, which reinforced the notion that analyzing large volumes of non-numerical data is viable with the help of Big Data technology.

In one respect, hospitality gaming has been a trailblazer in leveraging data technologies particularly as it relates to CRM. In other respects, the constant onset of new technologies and opportunities for refinement have posed a continuous challenge. While the debate remains open on Big Data usage being well developed in the hospitality gaming space, a distinction should be drawn between the exciting possibilities of Big Data versus the realities of managing it. The literature is only beginning to grow on why the ideals of data-driven change are seldom realized.
Data and Decision Making

Data-driven change implies that better decisions happen because they are based on evidence, and not intuition (McAfee & Brynjolfsson, 2012). Data-driven decisions resemble a more arcane concept of evidence-based decision making, which appears in the decision sciences. The concept of using data to drive decisions predates the modern personal computer and were linked to an era of punch-cards and large mainframe computers (Hein, 1967).

One of the biggest misconceptions of data mining is that it is a black-box solution that outputs the required answer—or decision for that matter—to any business problem results at the push of a button. While most analysts may recognize that this is not the case, this is not readily apparent to others. Intelligence is created from a process of data mining or the sorting through volumes of customer data in search of patterns using advanced statistical software packages (Hall Jr, 2001). The complexity of this task gave rise to the development of standardized practices in data mining (Wirth & Hipp, 2000).

For example, the CRoss Industry Standard Process for Data Mining or CRISP-DM was designed as a process to carry out data mining projects irrespective of industry. By standardizing the data-mining process, the goal was to provide some structure and guidance to those that are new to data-mining. The six steps in the process are: (a) business understanding, (b) data understanding, (c) data preparation, (d) modeling, (e) evaluation, (f) and deployment. Another example is SEMMA, which stands for Explore, Modify, Model, and Assess. SEMMA was developed by the SAS Institute and CRISP-DM was the brainchild of a consortium initially composed with DaimlerChrysler, SPSS and NCR (Azevedo & Santos, 2008). Standardized business processes such as CRISP DM and SEMMA helped to bring understanding to the fact that the analysis of vast amounts of data is actually the easier part of the whole process, given that the processing of statistical procedures is so fast with today’s technologies. The more challenging part is ensuring that the large quantities of data are clean, reliable, and appropriate to the analysis in the modeling phase—all taking place subsequent to the often overlooked preparation of the data (Pyle, 1999). While it is true that businesses can demand the simple conviction for data
systems to work as designed, it does not necessarily follow that the technology itself is easy to
setup; nor does it follow that these systems are black-box solutions that simply output solutions to
business problems.

Instead of focusing on technological challenges, the claim is made that too much attention
has been given to the idealized definition of analytics as “a process of transforming data into
actions through analysis and insights in the context of organizational decision making and
problem solving” (Liberatore & Luo, 2010, pp. 314). Analytics is also sometimes associated with
the term business intelligence. Chen, Chiang, and Storey (2012, pp. 1166) refers to business
intelligence and analytics as “techniques, technologies, systems, practices, methodologies, and
applications that analyze critical business data to help an enterprise better understand its business
and market and make timely business decisions.”

Provided all systems are operating as intended, senior executives and managers would be
tracking metrics in a more aggregate form. A Knowledge Management System (KMS) has been
defined as the broader vehicle that facilitates the sharing of knowledge for dissemination and
learning purposes (Brown et al., 2008). For some companies, this entails the development of an
executive information system (EIS). These systems are designed to produce state-of-the-art
graphics to produce easy access current information about the status of the organization (Brown
et al., 2008). The key deliverable at these levels is providing timely business intelligence
sometimes referred to as competitive intelligence. At a more operational level, where day-to-day
demands take priority, decision support systems (DSS) represent data-driven solutions for
mid-level managers. A DSS is an interactive system designed to assist managers in making
decisions incorporating data and data models (Brown et al., 2008).

Even with all the right analytical talent and key investments in data technology, capitalizing
on the intelligence still boils down to successful delivery of the product or service to the customer.
This assumes that both the technological infrastructure to support a fully functioning KMS, EIS,
DSS is operating as designed. This has been shown to be seldom achieved. Less than 28% of
firms in a survey of Fortune 1000 executives feel they have actually established this and seen
value out of their data-driven programs. The remainder have either started and not seen value, or not started at all (Bean, 2017, April). Despite the tools having been around for over a decade, industries continue to struggle with harnessing the potential of Big Data analytics despite the technology being readily available (Ayres, 2007).

**Social and Technological Complexity**

Putting Big Data analytics aside, change management by itself has been described as a complex social process, especially for larger organizations. Big data analytics requires specialized skills and large technology investments that corporate leaders may not fully comprehend. Data-driven change is therefore both socially and technologically complex. This could be classifiable as a ‘big hairy audacious goal’ (BHAG)—a term coined by Collins and Porras (1996) representing an ambitious vision taking upwards of ten to thirty years to fulfill. The authors noted that completing BHAGs should not be a foregone conclusion and suggesting a predetermined success rate at 50% to 70%. With continued challenges being reported in achieving data-driven change, the opportunity for filling research gaps became apparent, particularly with respect to the challenges of data, and less so the opportunities.

Authors and scholars have certainly addressed the inherent complexities in the challenges of data-driven change (Barton & Court, 2012; Datnow & Park, 2014; Glass & Callahan, 2014; Magnini, Honeycutt Jr, & Hodge, 2003; McAfee & Brynjolfsson, 2012). These authors are to be commended for their contributions to the research area in their summarizations on both the promise of Big Data analytics and its challenges. Furthermore, they have provided managers with useful step-by-step guides for implementing data-driven change. However, anyone familiar with data-driven change in today’s hospitality gaming space would agree that these guidelines have only come so far as widespread adoption continues to hamper change efforts (Rothberg, 2017, June 26). This runs in parallel with the assertion by Todnem (2005) characterizing existing theories on change as being overly prescriptive and lacking in producing valid frameworks. The goal of the current study was to prevent a similar destiny of overgeneralizing the difficulty of
data-driven change.

In addressing the gaps in the literature, it was concluded that the vast majority of extant literature on data-driven change applied a scope that was at the macro-organizational level. More exploration was needed in connecting the broader phenomenon of change to interaction level dynamics. What is known is that subnetworks of information and knowledge sharing amid broader networks make the change process a more complex phenomenon; and traditional organizational charts are limited in their capability to explain change. To this end, the current research employed the framework of exploratory social network analysis. Those unfamiliar with this school of thought may be interested to know broader change boils down to individuals changing at the interaction level. It was in this domain that existing research was determined to be underdeveloped.

**Difficulty of Change**

Data-driven change has been established as complex because it is both socially and technologically intricate. It is also known that data-driven change is difficult. However, to conclude that data-driven change is difficult simply because it is complex would be an overgeneralization. Before drawing connections between complexity and difficulty, it is also important to discuss the extant theories on why change is difficult.

**Resistance**

The concept of resistance is said to imply that humans tend to fall into certain habits and that because of that are resistant to change (Robbins & Judge, 2013). This view of resistance was disputed by Dent and Goldberg (1999) who claimed that resistance implies a psychological state, which is unfair in describing a more complex issue where situational factors could cause someone to maintain a status quo.

To this last point, an organization may have a natural inclination to keep mechanisms and procedures stable. The concept of structural inertia was pioneered within sociology by Hannan and Freeman (1984). It was suggested that organizations may face pressures to remain the same,
even in a turbulent and changing environment, and therefore have controls in place to encourage stability.

Another reason for resistance is that intended change, if not communicated and deployed thoughtfully, may have adverse consequences in different parts of an organization. In other words, as departments are working interdependently, applying change in one area may not take into account its impacts in other areas (Robbins & Judge, 2013). Change also entails doing things differently, which may be seen as risky. As a result, management may become indecisive and hesitate in making change happen (Brooks, 2011).

Dent and Goldberg (1999) discussed that a distinction needs to be drawn between thinking about change as a system or as an individual psychology. Dent and Goldberg (1999) argued that change theorists can improperly anticipate that resistance will automatically occur, and prescriptive measures are more reactionary in nature. Instead, change management should perhaps focus more on the prevention of resistance as opposed to the overcoming of it (Dent & Goldberg, 1999). For example, individuals may not be resistant to change, so much that the reward and organizational structures are not set up to incentivize change properly, and that there is a bigger incentive not to change, even in the presence of an outward desire to change (Ford, Ford, & D’Amelio, 2008). The authors suggested that resistance, for lack of a better term, is a form of engagement in the change process. The authors challenged that the resistance term is unfairly assigned pejorative meaning in the literature. Alternatively, resistance should be considered an exercise in sensemaking on the part of change agents engaged in a broader process of strengthening relationships within the organization.

The determination of resistance as a good or bad thing—and if it should even be termed that—remains unresolved. However, the discussions around resistance pointed to the idea that dynamics exist that prevent intended change from occurring in a purely harmonious way. this also suggested that because both organizational and individual factors are at play, change does not occur in a consistent manner whereby every individual adopts change in the same way and at the same rate.
Culture

Another commonly cited obstacle to change is culture. Mason and Pauleen (2003) found that knowledge management efforts are not automatically embraced and that there are barriers such as trust and cultural issues. Unlike resistance, which can imply individual psychology, the culture term is applied at the organizational level. It refers to social and economic ties that combine to form groups. Organizational culture refers to a system of shared meaning held by individuals that distinguishes an organization from others (Robbins & Judge, 2013). Not just comparatively to other organizations, cultural differences can also exist within organizations as well. There may be a broader culture that represents the corporation, but individual departments in large organizations tend to develop subcultures that include core values with some traits from the dominant corporate culture, but also include traits unique to the department or geography (Robbins & Judge, 2013).

Data-driven change does require companies to adopt a new culture; specifically, a culture of decision making as described by McAfee and Brynjolfsson (2012). This has proven to be an undertaking easier said than done. Bean (2017, April) concluded that the challenges for most companies are not related to technology, and that the biggest obstacles to widespread adoption are more cultural in nature.

Scholars would agree that culture, like resistance, can be wielded in some ways that are value-added and other ways that are not. Barney (1991) foresaw the potential of data collection of social and behavioral phenomena as a way of determining the value of firm resources. It could be inferred that social complexity, including interpersonal relations and culture may not maximize efficiency. In this vein, issues such as conflict, employee turnover, and upward mobility if not managed in a way that is perceived as a net positive by employees, could be deemed as less than efficient. This then creates an opportunity for improving optimization. To this end, outside consultants are often tasked in assisting with change efforts under the guise that an objective perspective would be helpful to those inside the organization looking to gain efficiency. This however can backfire, as the outside consultants may not have the cultural familiarity to advise on
change (Robbins & Judge, 2013).

**Knowledge Transfer and Organizational Silos**

Another hindrance to intended change that has received some attention relates to organizational structure. Organizational silos have been identified as challenge to the process of knowledge transfer. This transferring process is a component of knowledge management (O’Dell et al., 1998) and also arises in literature related to organizational learning. Tett (2015) explored how the stifling of knowledge within silos can lead to inefficiencies. The author documented how one Wall Street firm was able to identify (and capitalize upon) lagging changes to commodity prices across different brokerages offering the same thing. This imperfect transfer of knowledge was attributed to the way the brokerage was structured. Tett (2015) summarized that actors behave strangely when they are bound by a heavily siloed organization because it creates competition. In another illustration, Tett (2015) highlighted how Sony was too rigid in their structure and this prevented them from adapting more quickly into open platforms, which was subsequently captured by Apple in dominant fashion.

Goh (2002) found that effective knowledge transfer is critical to gaining competitive advantage. The author identified subtle behavioral traits, rooted in political motives, which may cause individual actors to hesitate in participating in the knowledge sharing process. Goh (2002) also identified information technology as playing a key role in the knowledge transfer process. Additionally, matching the process to the type of knowledge was also found to be important (Goh, 2002). The forum in which the knowledge transfer takes place is also said to play an important factor. Within the field of hospitality, Yang (2009) found that managers prefer spontaneous face-to-face interactions for knowledge transfer; this was preferred over planned social times. This discovery helped to explain that managers were found to have a shortage of time, and that learning ‘on the fly’ was not uncommon, and also preferred. Goh (2002) concluded that more research is required in understanding the soft factors of the knowledge transfer process and that too much emphasis has been placed on the information technology and structured processes.
To these points on knowledge transfer, data-driven change may require a unique type of relationship between actors and related technologies. Further, to the point of having the right culture for knowledge transfer, Goh (2002) advised a problem-seeking and a problem-solving culture. The claim is that fostering an innovative culture is important to knowledge transfer. However, it does not necessarily follow that data-driven change can be grouped together with all forms of knowledge transfer. To this point, the current study sought to consider the unique aspects of data-driven change. In this process, conclusions drawn by Goh (2002) and Tett (2015) help to illustrate that environmental, structural, and hierarchical factors are important to consider when contemplating theory related to the difficulties of knowledge transfer and organizational change.

Collaboration and Facilitation

How then should the difficulties of change be addressed? Understanding culture and resistance may help change agents in identifying the challenges of data-driven change, but they should also be familiar with the established concepts. This section explores the existing literature on collaboration and facilitation, which are important to the scope of the research design addressing change more at the interaction level, rather than solely at the macro-organizational level. These concepts also served as important precursor concepts to analytical bonds (AB)—a hypothesized concept developed in the current study introduced at the conclusion of this chapter.

Collaboration. Collaborative linkages have been found to be important to the diffusion of change. The concept arises in the literature on the diffusion of knowledge and innovation (Camarinha-Matos & Afsarmanesh, 2005). These linkages are defined by a voluntary arrangement between independent entities to share resources including processes and technology (Ahuja, 2000). It has also been characterized by sustained, focused, and intense interaction (Auster, 1992). These interactions are frequent, require coordination, close contact, focus on specific objectives and involve mutual dependencies (Gulati & Singh, 1998).

With respect to the broader network context, Singh (2005) inferred that the diffusion of knowledge occurs more effectively within the confines of an interpersonal network, even more so than regional or intra-firm networks. With a variety of network parts involved, collaboration also
implies a certain diversity (Nieto & Santamaria, 2007). To this point, collaborative networks are characterized by heterogeneity in terms of their operating environment, culture, social capital, and goals (Camarinha-Matos & Afsarmanesh, 2005).

**Facilitation.** While collaboration involves stakeholders that are already a part of the firm, facilitation has been defined as a process where an outside person with no decision making power, is recognized by the group to assist in problem solving or decision making (Wardale, 2013). In a way, this distinction between collaboration and facilitation reflects the concept of internal versus external consultancy. Depending on the situation or problem, either bringing in someone from the outside or looking within an organization must be considered (Crowther & Lancaster, 2012).

One of the practical implications noted in Wardale (2013) is the idea that facilitation is more likely to be effective if the participants share a common language. This is noteworthy for hospitality gaming as there can be a cultural divide between front-of-house and back-of-house operations (Rothberg, 2017, June 26). In this sense of assimilating towards a shared language, facilitation can be viewed as a process of workplace learning. Ellinger and Cseh (2007) performed a qualitative analysis of interview data from a customer-service firm. When looking for catalysts for facilitating learning, the theme of seeking expertise was identified in the data. This is relevant to the role of analytics, as this business function can be seen as highly specialized.

Whether it is an inside or outside agent facilitating change, and if the development of common language and workplace learning is involved, the difficulty of change implied that resources will be expended in the change process. To this point, facilitation was also addressed in the literature as a process of matching resources to activities, specifically the activity of problem solving (Woiceshyn & Falkenberg, 2008). The authors made a connection between facilitation as a part of critical problem solving and value creation. In their study on petroleum exploration where a diverse group of experts are required to coordinate, one of the roles of scientists was to facilitate knowledge sharing. Also, internal networking inside the firm was highly encouraged (Woiceshyn & Falkenberg, 2008). This article also focused on knowledge-gathering networks. Of particular interest was the concept of firm-level networks that can arise from formal seminars and
intranets devised by the firm’s leadership (Woiceshyn & Falkenberg, 2008).

Sharing, gathering, facilitating and collaborating around knowledge at the interaction level and across a diverse range of stakeholders appeared to be important to data-driven change; especially given the specialized knowledge and business impact it involved. However developing a common language in the face of resistance seemed to be an improbable goal, but to what degree? This question led to the conceptualization of analytical bonds; a unique type of interaction specific to data-driven change.

**Analytical Bonds (AB) and Analytic Facilitation (AF)**

Resistance and cultural problems have long been identified as reasons for why change is difficult. Data-driven change has been said to be difficult for similar reasons (Bean, 2017, April). For this study, the notion that data-driven change is consistent for the same reasons as change in the broader context appeared as a gap in the literature.

It has been argued up to this point that data-driven change is complicated by the idea that it is a feat that is complex both socially and technologically. Complex to the degree that specialized knowledge in subnetworks when not managed properly, can result in adverse consequences (i.e. Enron). Traditional organizational charts are limited in their ability to illustrate the change process as a socially complex process. Therefore, deeper understanding of the difficulty of data-driven change is needed that goes beyond the often noted challenges of culture and resistance.

One study on Big Data analytics provided a useful starting point for understanding the nuances that differentiate data-driven change from garden variety change. McAfee and Brynjolfsson (2012) noted that in traditional strategic decision making, companies often make most of their important decisions by relying on the HiPPO or the highest-paid person’s opinion. The authors expressed that businesses rely too heavily on experience of said HiPPOs and not enough on data. In a data-driven world, analysts and technicians are now in some ways the gatekeepers of the specialized strategic knowledge. This unique dynamic between analysts and superiors required more attention. Scholars have overlooked the tensions that may arise between analysts and superiors—and for that matter, between analysts and any high-ranking leader.
In fairness to what has been written in this regard, McAfee and Brynjolfsson (2012) did urge leaders to ask critical questions about how analysts arrived at their conclusions as well as mentioned the importance of allowing themselves to be overruled. However, scholars would challenge that this requires a certain humility. In *Good to Great*, a popular book on change, Collins (2001) suggested that strong change management leaders are grown from within the company, and don a certain humility. These are the leaders that have shown to be the best positioned to lead companies into greatness. McAfee and Brynjolfsson (2012) and Collins (2001) are surely right about having a certain type of leader to lead data-driven change but as the authors may not have foreseen, recent studies have shown that today’s tech giants that leverage data for financial gain are a far cry from such humble ideals (Bean, 2018, April 25; Cobbe, 2018; Pentland & Shrier, 2018, April 11).

Through this gap in the literature, there was a theoretical argument to be made that extended from the HiPPO dynamic and into a network framework. The argument being that data-driven change involved some interaction (or network tie) whereby specialized knowledge used to inform strategic decision making was transferred to a higher-ranking decision maker. This rested on the premise that the analyst who creates new knowledge through analysis and data interpretation is often not also the final decision maker.

Furthermore, this unique interaction implied a sender-receiver dynamic whereby the sender provides specialized knowledge and the receiver accepts the knowledge and applies it to a strategic decision to be made. Thereby, the receiver in some way entrusts some of the decision making to a lower ranking person, albeit indirectly. Naturally, it also followed that the sender-receiver dynamic involves a process of encoding and decoding between a sender and a receiver as well as a channel upon which the message is transmitted; an organizational communication concept originating from Robbins and Judge (2013). However, a theoretical distinction was drawn such that there is an exchange of specialized analytical knowledge for the relinquishing/entrusting of formal decision making power, which is different from communication by itself. This was posited as an analytical bond (AB), a term coined for the
current study to represent an interaction distinct to data-driven change.

It is concluded that data-driven change required trust and communication between analytic stakeholders. In this sense, the concept of AB may seem trivial, but it is in fact a crucial piece in terms of theoretically describing the difficulty data-driven change. Aside from the AB interaction (tie), the question can be raised as to the description of the individuals (nodes), whom are engaged in an analytical bond. What is it about the actors that would constitute a strong or weak AB? As seen in the next chapter, not only does analytic facilitation (AF) play an important role in forming strong bonds, but also, it brings with it the ability to apply measurement to the broader problem of data-driven change.
CHAPTER 3

Mixed Methods

The literature review produced an additional theoretical lens in network analysis to examine change as a diffusive process with respect to the social complexities of change—this was not considered to be achievable using just a traditional organizational chart. Correspondingly, analytical bonds (AB) was introduced as a specific kind of interaction related to data-driven change. This concept was developed in response to gaps in the literature implying that resistance and cultural factors have only come so far in explaining why data-driven change is difficult. The broader criticism being that change management research has been criticized as being overly prescriptive, contradictory, and lacking in valid frameworks Todnem (2005). Taking these points together, it was concluded that an examination of change at the micro-interaction level was appropriate, as opposed to a more macro-organizational level. Data-driven change as a social process whereby leaders are working closely with analysts to make big decisions pointed to the need for rich qualitative data. However, quantitative research methods were also embedded to broaden the research design. This was done partially in response to the point made by Todnem (2005) about a lack of measurement in change management research. Several iterations of research designs were developed under the guidance and feedback of the dissertation committee. Ultimately, a mixed-methods methodology was developed and concluded as a good fit for the research questions.

Methods Background

Considered the third ‘movement’ or ‘paradigm’ of science following the developments of quantitative and qualitative method, mixed methods arose from the demand for multiple forms of evidence as well as more sophistication in evidence. To fit the needs of policy makers, practitioners and other applied areas, the early pioneers of mixed methods research felt that certain research problems cannot rely only on numbers by themselves to explain phenomena in the quantitative sense and words in the qualitative sense (Creswell & Clark, 2007). The specific
kinds of research questions that are best fit for mixed methods may fall into one or several of the following categories of needs: (a) one data source may in insufficient, (b) a need to explain initial results, (c) a need to generalize exploratory findings, (d) a need to enhance a study with a second method, (e) a need to best employ a theoretical stance, (f) and a need to understand a research objective through multiple phases (Creswell & Clark, 2007).

Throughout its history, several formal definitions of mixed methods have been put forth. The core definitional characteristics that are applicable to the current study is that both quantitative and qualitative data are collected and analyzed; both forms of data are mixed through a process of integration; and the research procedures are framed accordingly to philosophical worldviews and theoretical lenses (Creswell & Clark, 2007). The research questions for the current study addressed why data-driven change is difficult in hospitality gaming as well as how theory and measurement can be applied to this problem. Because data-driven change has been often cited as a problem of culture and resistance, an organizational behavior research lens was applied. This fit well with qualitative methods. Data-driven decisions are unique in that the responsibility of making strategic decisions do not completely fall into the hands of those with the most formal power, a social network framework was applied as a theoretical framework. Network analysis involves numerically driven concepts and the quantitative instrument in the current study provided a means of predicting and measuring a behavior that was related to the research questions. This quantitative component was embedded within a classical grounded theory research design; in embedding the instrument, the qualitative methodology was designated the priority research stream.

**Grounded Theory**

The process of grounded theory is focused on developing categories that illuminate the data (Cassell, 2015). Grounded theory is appropriate for studying interactions because the methodology was designed to focus on micro-level processes reflected in action and interaction (Locke, 2001). Grounded theory is described as a general methodology for developing theory that
is grounded in data that is systematically gathered and analyzed (Strauss & Corbin, 1994). In more straightforward terms, grounded theory seeks a general explanation of a process (Creswell, 2015). Grounded theory refers to both the method and the outcomes of the research process. It consists of a “specific set of procedures for carving out the inbuilt middle-range theory from and with the help of the empirical data” (Eriksson & Kovalainen, 2015, pp. 197). It can also be described as a highly developed idea of formally named and described procedures. It involves both induction and deduction, and the theory develops and evolves during the research process, resulting from constant data collection and analysis.

Theory is derived from data acquired through interviews, observations and documents, and the analysis is systematic and begins as soon as data becomes available. Glaser and Strauss (1967) and Strauss and Corbin (1994) represent some of the pioneering work in this area. Grounded theory has philosophical roots in American pragmatism and is informed by the ‘Chicago Schools’ and their qualitative approaches to the study of group life (Locke, 2001). As a departure from the symbolic interactionist approach that was focused on description through observation, Glaser and Strauss (1967) argued that sociologists must also generate formal theories out of their data collection (Locke, 2001).

To ‘ground’ theory in qualitative materials not limited to academic literature, is to apply a set of strategies for conducting rigorous qualitative research (Charmaz & Belgrave, 2007). Grounded theory represents a marriage between the research process and theoretical development (Charmaz & Belgrave, 2007). Similarly, grounded theory blurs the lines between data collection and data analysis (Charmaz & Belgrave, 2007).

While the broader research design is qualitative in nature, this study also employed a quantitative instrument, which thereby made this a mixed methods. Applying mixed methods brought with it some important philosophical issues that were important to address in the research design. This chapter continues with a discussion on the assumptions related to knowledge and philosophy. This is considered an important step as mixed methods continues to evolve from its formative years where paradigms where being debated, to its more recent expansion and
development all of which occurred just over the last half of the twentieth century (Creswell & Clark, 2007).

**Epistemological Assumptions**

Within its short history, mixed methods has several philosophies upon which it draws upon for conducting research (Creswell & Clark, 2007). Philosophical assumptions consist of a basic set of beliefs that guide inquiries, and is also referred to as a worldview or paradigm. There are several worldview possibilities when it comes to mixed methods including postpositivism, constructivism, participatory, and pragmatism. Despite the approach remaining inherently mixed and it is accepted that tensions will arise as no single philosophical stance by itself is watertight, the goal is to address general philosophical orientations to research (Crotty, 1998).

In the qualitative portion of the current study, a constructivist worldview was adopted for this research, which is often found in studies involving grounded theory (Mills, Birks, & Hoare, 2014). Constructivist grounded theory suggests that meaning is located within the mind of the individuals (Charmaz, 2000). Constructivism, typically associated with purely qualitative approaches, assumes that meaning of phenomena, formed through participants and their subjective views, make up an overall worldview. Participants provide their understandings and speak from meaning shaped by their social interactions from their own personal histories (Creswell & Clark, 2007). Research is shaped from the bottom-up; from individual perspectives to broad patterns leading up to broader understandings.

As the design shifted to the quantitative instrument, the pragmatist worldview was adopted. Pragmatism is commonly associated with mixed methods research and many authors consider this worldview the ‘best’ for mixed methods (Creswell & Clark, 2007). Here, the focus was on the outcomes of the research, and the primary importance of the question being asked rather than the methods. To this end, the following research question is relevant: How does theory inform the challenges of data-driven change? The use of multiple methods of data collection were used to inform the problem under the study so therefore, the pragmatist worldview allowed for pluralism
and is oriented to ‘what works’ in practice (Creswell & Clark, 2007).

The shift in philosophical worldview was important to address as Greene and Caracelli (1997) recognized that different paradigms can give rise to contradictory ideas and contested arguments. Tensions that occur from qualitative-quantitative mixing reflect different ways of knowing about and valuing the social world (Creswell & Clark, 2007). By being explicit about these philosophical oppositions, this ‘dialectical’ perspective honors but cannot reconcile all assumptions that may otherwise be possible in a single method study operating within a singular worldview.

Establishing parameters around validity is therefore essential to then assess the reliability and generalizability of data. Collins (2015) discussed some guidelines in addressing multiple validities that occur in mixed methods. The goal is to achieve integrative efficacy whereby the integration of quantitative and qualitative methods by the researcher leads to the forming of consistent inferences derived from findings produced by a careful and thoughtful research design. Validity and rigor are key to producing high-quality research. However, this term is subjective depending on the community in which the research is being evaluated. Highly generalized concepts that are too abstract are viewed with suspicion with respect to both quantitative and qualitative research. The suggested approach is to demonstrate rigor by lending credence to validity measures relevant to both quantitative and qualitative paradigms (Collins, 2015).

Within quantitative research, statistical validity is essential. Potential threats to causation and generalizability can be addressed by applying internal and external validity measures. Measurement validity is also important to the quantitative paradigm and is closely related to establishing construct validity that demonstrates evidence based on the internal structure of the data provided by the measurement instrument (i.e. factor analysis) (Collins, 2015).

Within qualitative research, Collins (2015) noted three critical dimensions for establishing validity. The first dimension relates to trustworthiness in the research procedures designed to acquire understanding of the phenomenon. This includes detailing procedures that establish credibility, transferability, dependability, confirmability in the qualitative data collection process.
The second dimension relates to the detection of bias, or authenticity in the reporting of findings. This includes applying measures that establish fairness, or the degree to which collected data represent a balanced perspective that involves the participants’ constructions and their underlying worldviews. Authenticity also encompasses the notion that participants involved in the research are themselves evolving on their perspectives of the research topic and this may occur as the data is being collected. The third critical dimension relates to reflexivity, or the researcher’s ability to reflect critically on the self as a researcher. Reflexive strategies including journaling, reflective memos, and data triangulation, which can enable the researcher to heighten their awareness of their own biases based on their own backgrounds. Applying these critical dimensions to data collection and analyses are critical to establishing validity in the qualitative research domain.

It can be argued that personal experience on the part of the researcher may influence or bias the interpretation of the data. Though personal experience and objectivity seem to be at odds with each other in an empirical research paradigm, those unfamiliar with qualitative inquiry may be surprised to find out that addressing biases in analysis is part of the process. Procedural integrity issues should be scrutinized regardless of whether the research is quantitative or qualitative. One of the purposes of grounded theory is to triangulate multiple vantage points including qualitative data and literature while maintaining a heightened sense of personal biases; all the while, carefully addressing validity issues in the process through documentation via reflective memos and journaling.

Some of the advantages of grounded theory is that it is rooted in a different kind of validity based on procedural integrity and intense and reflexive journaling of processes and methodological procedures. However, for that same reason, qualitative research is not validated by any statistical rigidity, which is important to business managers and practitioners: one of the intended audiences of this study. As with many business problems, quantitative measurability is often times the goal.

By offering a set of systematic procedures, grounded theory enables qualitative researchers to generate ideas that may later be verified through traditional logico-deductive methods. While
the goal of grounded theory methodology is theory creation, the aspirations of the theory is to create something that would eventually be empirically valid by statistical standards—the kind of validity familiar to most. To this point, the embedded survey instrument was designed to fit the research questions. It was also beneficial in providing some insights into the potential for applying scales to the developed theory.

**Embedded Research Design**

Within the mixed methods literature, there are numerous approaches to mixing quantitative and qualitative research strands. A strand is a component of a study that encompasses the basic process of conducting quantitative or qualitative research including research questions, data collection, analysis, and interpretation (Teddlie & Tashakkori, 2009). Because there are so many possibilities, Morse (2003) established a notation system to describe the various mixed methods procedures. The current study can be expressed as QUAL(quan), with the capitalization notating the priority of the research stream, and the parentheses indicating that one stream is embedded within a larger design.

The embedded design is a mixed methods approach where the data collection and analysis of one type occurs within a broader traditional design (Creswell & Clark, 2007). In this research, the quantitative instrument is embedded into the broader grounded theory qualitative research design (Figure 2). Creswell and Clark (2007) noted that social network analysis research—relevant to the current study—as being an appropriate use of the embedded design. The embedded design is used to enhance the application of a traditional qualitative or quantitative design.

The design for the current study also reflects an emergent design. As opposed to a fixed design, the emergent design generally occurs when a second approach is added after the study is underway because one method was found to be inadequate (Morse & Niehaus, 2009). This reflects dynamic approaches to mixed methods that considers and interrelates multiple components of research design rather than placing a focus on selecting an existing typology.
Figure 2. Embedded mixed methods design.
**Issues**

One of the advantages of the embedded design is that it allows the researcher to improve the broader design as well as allow for different but related research questions to be explored (Creswell & Clark, 2007). One of the disadvantages of the embedded design is that the researcher must specify the purpose of collecting one data set as part of a larger study. Furthermore, the researcher must decide at which point in the study to collect certain data. The integration of the two strands must also be considered carefully because the qualitative collection may introduce potential treatment bias that affects the outcomes of the experiment (Creswell & Clark, 2007).

**Instrument Development and Validation Variant**

There are variants of the embedded design depending on if one method is supplementary to the other (Creswell & Clark, 2007). The variant used in this study is referred to as an embedded instrument development and validation variant (Plano Clark & Galt, 2009). Here, the quantitative strand was supplementary to the qualitative design, and the survey was a means to pilot test a potential measurement relevant to the grounded theory and provide additional evidence that the instrument could be used to produce meaningful outcomes as outlined by Creswell and Clark (2007).

**Qualitative Strand**

In this research, the qualitative research strand had priority over the quantitative stream. In total, there were three qualitative data components that were collected to ground the AB and AF constructs. This included the literature, reflective memos, and interview data. Locke (2001) and Glaser and Strauss (1967) has advocated for the ‘triangulation’ of data from multiple sources. This does help to provide different vantage points from which to develop conceptual categories (Locke, 2001). The reflective memos were collected over the course of seven and a half years as an industry professional. Originating from daily agendas and meeting notes, these memos were used to inform the literature review, the interview protocol, and the overall research design.
Through data triangulation, the goal is for collected data to illuminate a process (Charmaz & Belgrave, 2007).

**Quantitative Strand**

The quantitative research strand was a supplemental role in the broader qualitative design. The introduction of a survey was a reflection of the emergent design and developed as an embedded instrument to the broader qualitative grounded theory design. The usage statistics data itself could have been validated internally through interviews with managers inside the organization discussing individual users and their usage statistics. However, to achieve external validity, a survey was designed for known users of analytic solutions. Their survey results were matched up to their usage data for analysis thereby providing external validity to the tested hypothesis that usage statistics are a significant predictor of AF.

**Mixing**

This mixed methods design featured an interaction between the two strands of the study, whereby both research questions were addressed to varying degrees by the quantitative and qualitative strands of this study. This is referred to as the point of interface, and is also referred to as the stage of integration.

The interaction of strands occurred in two places. First, at the level of data analysis. The researcher first analyzed the data from the qualitative strand as a separate activity from the quantitative analysis. Only through the interactive strategy of merging, did the researcher bring the two sets of results together through a subsequent combined analysis (Creswell & Clark, 2007).

The other interaction of strands occurred at the design level such that the supplemental quantitative design was embedded within a larger qualitative design. The embedded method was conducted in such a way to fit the context of the larger qualitative inquiry (Creswell & Clark, 2007).
Hypothesis Testing

The purpose of the qualitative strand was to develop new theory on the difficulty of data-driven change. Additionally, one of the questions in the interview was designed to elicit a yes or no response, which could be used to test the null hypothesis (H1). With respect to the quantitative strand, the analysis also tested two other hypotheses. The factor analysis tested the null hypothesis H2 below and the subsequent regression analysis tested the null hypothesis H3 below.

\[ H1_0: \text{Data is not utilized more effectively in some conversations than in others.} \]

\[ H2_0: \text{The AF construct cannot be explained in a reduced number of factors.} \]

\[ H3_0: \text{Usage statistics are not a significant predictor of AF.} \]

Data Collection and Institutional Review Board

Both quantitative and qualitative data collection involved human subjects. Based on the research protocol, exempt approval was attained through the University of Nevada Las Vegas Institutional Review Board. Reflective of the emergent qualities of the mixed methods design, the approval process also included four separate package submissions and a modification request. IRB exempt status was granted on May 18, 2018 (Appendix 3).

Privacy and confidentiality. To protect the subjects, no identifiable personal information was shared. The interviewees were allowed to choose the location for the interview. The interview required that the interview take place in a private setting. For the in-person survey on employees, this took place in a private designated area of the casino and only one participant was surveyed at a time. All subjects were informed that the research design was intended to protect the privacy of the participant and ensure the confidentiality of the content.

Risks. There was very little potential risk involved in this study. Questions in the interview related to data-driven change were framed to discuss the concept in a broader sense. There was no requirement to discuss specifics related to the identities of employers. The interviews took place at a site agreed upon by the interviewee. The in-person employeesurvey
took place on company grounds where facility authorization letters were ascertained. It was very unlikely that any emotional, physical or social harm will come to any study participants, which included the researcher.

For the reflective memos collected by the researcher, the data collection was focused solely on concepts that inform the theory advanced in the paper. Any description of the data in the research was generalized. Selected data did not include names of individuals or projects; this level of detail was not required for the purpose of the study. With respect to the interview data, the informed consent form was reviewed prior to the interview. All survey responses were collected anonymously and only the researcher and principal investigator had access to the data. The recordings were saved on a secure hard drive on the researcher’s laptop computer and transferred immediately to a secure computer server. The files were never exposed to the cloud or internet. Consent process was clearly discussed with the participant. If any direct quotation from the interviews was to be included in the draft, member checking was performed with the interviewee to not only inform the participant, but also, to ensure the individual that the manner in which the quotation is presented in the research is consistent with the source. The data from the in-person survey was sealed on the site after all the data has been collected. The usage statistics were delivered to the researcher as printed data by hand in a sealed envelope. All data was taken to UNLV for data input and analysis. All interview and in-person survey data was destroyed upon completion of the study in October 2018.

**Reflective Memos**

From the researcher’s work experience at a diversified gaming corporation, hundreds of work agendas and reflective notes were documented. Data was collected both as printed papers, journals, notebooks, and as Microsoft Word documents. These documents reflected bulleted items representing talking points in meetings. A bulk of the meetings were weekly progress report meetings conducted by senior corporate leadership. Within these meetings, notes and reflections were written either in the margin by hand or typed as additional text to Word documents. Other
meetings included those related to projects occurring among corporate team members as well as projects that involved areas outside of the immediate area. This included other functional areas of corporate as well as property level managers. These notes and personal memos were used to inform the research design including the literature review and the interview questions.

**Interview Data**

In total, 25 subjects were interviewed. The research subjects included managers and executives that have worked in hospitality and gaming and are 18 years of age and over. To be included, the participant had to have worked in a managerial capacity for at least five years. As for recruitment, a form letter was sent out to potential participants via email and LinkedIn messaging. A convenience sample of personal contacts was used to select the participants. Employees that report directly to or were subordinate to the researcher were excluded from the research. Snowball sampling for the interview was also conducted. At the conclusion of each interview, the subject was asked if there were anyone they would recommend for the study. If there were recommendations, a flyer was distributed, which was then sent to the person or persons that were being recommended. The semi-structured interview lasted approximately 15-30 minutes and consisted of six questions. The participants were encouraged to raise questions if they had any concerns throughout the interview.

**Interview protocol.** Each interviewee received a recruitment form letter prior to the interview. Once the participant agreed initially to participate, the interview location and time was arranged. At this point, the interviewee was briefed on the informed consent process prior to the interview taking place. If the participant understood the consent process and the nature of the research, the participant was given the option to participate or withdraw from participation. A copy of the form was also provided to the participant for their reference. The interviewee then confirmed their participation in the interview by signing the informed consent form.

**Interview questions.** The first two questions were designed to elicit qualitative data that supported the research problem. The third question was designed to directly test a hypothesis and provide construct validity. The fourth and fifth questions were related to interview protocol
allowing the interviewee to ask questions and lend any additional insights to the study (Appendix 2). The final question was for the purpose of snowball sampling. The interview questions originated from other qualitative data and the literature review. All interview data was transcribed for analysis. The questions were as follows:

1. What are the skills that define an effective analyst?
2. Describe the relationship between the responsibility to learn more about analytics, and the responsibility to make analytics easier to understand for others?
3. Do you think data is utilized more effectively in some conversations than in others?
4. Is there anything that you feel we have not covered that you think would be pertinent to this area?
5. Do you have any questions for me?
6. Finally, is there anyone you would recommend for interviewing that would be useful to this study?

**Survey**

The purpose of the survey was to test an embedded measurement instrument. The survey was conducted on employees at multiple casino properties, with permission from the facility. The survey consisted of 20 Likert scale questions (Appendix A). These questions were derived from the literature review as well as the reflective memos. The survey was performed in-person and each question was read out to the participant and explained further if questions were raised. The questions were sequenced in such a way that the hypothesized construct of AF, which dealt with getting involved in data-driven change, were asked last. This final section was made up of four questions. Three of them were formulated by the researcher. The questions designed for the current study included:

1. I would combine certain data across different reports.
2. I would want to get involved in changing the report content.
3. I wish there were more training on certain reports.
The final question that asked about the employees perceptions as to what degree the company makes key information available to employees is related to the concept of organizational learning. This question originated from Spicer and Sadler-Smith (2006) and was considered similar to the involvement concept in AF.

The preceding 16 questions were all drawn from literature. These questions were drawn from areas that deal with the general idea of employees interacting with technology solutions. The first block of four questions related to self-efficacy and asked the respondent about their comfort and self-confidence in using reporting solutions. This block was placed first to help because they were the most general in nature as it related to report usage and was designed to familiarize the respondent with the general area of questioning that was to follow. These questions were derived from Lin and Huang (2008), Kim and Lee (2006), and Kuo and Lee (2011).

The second question block related to information access and quality. This block of questions was designed to elicit feedback about report performance and allow the respondent to feel comfortable in understanding they are allowed to provide feedback on report performance and reliability. These questions were adapted from Kim and Lee (2006) and Popovič, Hackney, Coelho, and Jaklič (2012).

The third block of questions originated from Kuo and Lee (2011) and related to task-technology fit. These questions asked about how useful employees find the reports. The fourth block of questions relate to knowledge sharing, which most closely resembled AF. These questions were derived from Tohidinia and Mosakhani (2010). Because of the similarity to the AF concept, the knowledge sharing questions were placed just prior to the final set of questions.

**Sample.** The sample was composed of 49 casino employees that utilize reporting solutions in their day-to-day jobs. Selected respondents were required to work at a casino and used reporting solutions. The recruitment procedure involved working with the facility management team to determine which staff used reporting solutions in their day-to-day jobs. Once the management team determined the employees that use reporting solutions, a schedule was set for the in-person surveys. The employee was prompted by their manager to inform them that there
is a research study taking place on their reporting usage, and specifically mention that this does not relate to their job performance. Each employee was surveyed in-person one at a time by the researcher in a designated area of the casino. Each in-person survey took between 5-15 minutes. Prior to the survey, the researcher went over the informed consent process with the employee to make sure that the employee understood that their participation was voluntary and not required.

**Usage Statistics**

Usage data was also provided to the researcher from the company. This data showed how many times an employee used a business reporting solution. The sample included usage statistics for 49 employees. This data included the names of the employee so that the researcher could match that data to the survey for analysis. Once the survey data and the usage statistics were matched, the data was anonymized.

Data was made available on the employee’s overall usage and the number of distinct reports. Data were also provided on individuals as it corresponded to their usage on individual reports, not just in aggregate. Demographic data was not collected for this study as variables such as gender and age were not pertinent to the research question. The usage data was collected over the most recent six month period ending in May 2018. This period was selected to reflect the most recent data.

Data was also anticipated to contain heterogeneity because there were many types of employees that used the reports. Furthermore, there were many kinds of reports that were made available to the employees. As participation was voluntary, there was no assurance in the size and consistency of the participant sample.

**Analysis Procedures**

It should be noted that within grounded theory, there is overlap between data collection and analysis (Charmaz & Belgrave, 2007). The following section describes these overlaps in greater detail. The qualitative strand is described first followed by the quantitative strand, which was supplementary to and embedded within the qualitative design.
Qualitative Strand

A thematic analysis was performed with three stages of coding. The first phase was open coding, where the process was to uncover, name and develop concepts based on similarities and differences through a close analysis of text. The goal in this stage was to produce initial concepts that fit the data. The second stage was axial coding, which consisted of a closer analysis within each of the categories resulting from the first phase of coding. It is here where cumulative knowledge was developed to inform subcategories within the individual categories as well as their relationships to each other. The aim was to make explicit connections between the categories and subcategories and develop a fuller picture of the process of data-driven change. In the last stage, selective coding was performed. This was a process of integrating and refining the analysis and selecting one core category to form a larger theoretical scheme. A core category formed the focus around which all other categories and subcategories were connected by. The objective of selective coding was to explain the data via a core category.

The process of constant comparison also occurred, which is described as the iterative process of naming, comparing, and delimiting the theory as informed by the data as a means to further ground the theory (Locke, 2001). Comparing also helps the researcher to develop a common name or category for multiple observations in the data and moving towards the creation of more general conceptual categories.

Occurring in tandem with constant comparison was the process of naming. Here, the researcher attempted to conceptualize and develop abstract meaning for the observations or incidents in the data by articulating what was perceived to be happening (Locke, 2001). In the early stages of coding, data incidents were named in as many ways as possible, as the ‘ultimate’ meaning would be settled over the course of the analysis through comparison with other data (Locke, 2001).

Theoretical sampling was also employed where the selection of qualitative data was based on what is most likely to enable theory development (Cassell, 2015). Theoretical sampling occurs when the researcher selects data as the theory emerges (Draucker, Martsof, Ross, & Rusk, 2007).
Finally, for data confirmation and clarification, member checking was also performed whereby all interview participants were contacted after the study to be informed as to which excerpts from the interview were included in the study. Member checking is deemed an important routine in qualitative research, particularly in research designs where the participants are collaboratively engaged with the researcher (Creswell & Miller, 2000). All of the interview participants were active and experienced leaders in the industry; all of them invested in the benefits of value-added change. Member checking is particularly applicable to research involving collaboration as it represents the most important technique for establishing credibility (Lincoln & Guba, 1985).

None of the member checking resulted in any removal of data from the study, and only two of the 25 interview participants chose to clarify their statements. Brackets with all capital text were used to indicate [REVISED TEXT], a notation for transcriptions adapted from MacLean, Meyer, and Estable (2004). Brackets with regular case [like this] were used to indicate that the transcript was clarified, but not revised any further by the interviewee through member checking.

Quantitative Strand

For the survey, the Likert response choices included: strongly disagree, disagree, neither disagree nor agree, agree, and strongly agree. A sixth option was provided indicating the question is ‘not applicable’ to the respondent. Each survey was assigned a unique identification number and for each question, the scale was coded from 1 to 5. Despite their numerical values, Likert items are considered categorical variables and were treated in analysis accordingly. The survey population was selected because they have known usage statistics in the reporting solutions. These usage statistics were provided by the company and were matched to the survey data for analysis.

Factor analysis. The first procedure was to take the responses from the twenty survey questions and perform a factor analysis to determine if there was any structure in the data and to reduce the data to a smaller set of factors. The significant factors were analyzed for structure and constructs were developed based on an analysis of the rotated factor loadings. The factor scores were saved and output to the original respondent.
Regression analysis. The second procedure was performed to see if there was any significant relationship between the factors resulting from the factor analysis and the usage data obtained from the company. These variables were input into a regression model to determine if usage statistics could reasonably predict the theorized factors. Factor scores are often input and independent variables to predict a dependent variable. In this situation, exploratory factor analysis was used to assess the validity of the AF construct. This construct was then treated as the dependent variable to see if usage statistics can predict AF.

Merged Results and Analysis

The qualitative results were used to inform the theory development around data-driven change and AF in line with grounded theory methodology. The quantitative results were merged into the grounded theory as a means for understanding how AF can be measured through usage statistics as well as conceptualizing the measurement’s role within the broader context of data-driven change.

In conclusion, by applying a mixed-methods research design, the current study examined the possibility that resistance and cultural challenges were merely symptoms of a deeper issue. The assertion here was that grounded theory analysis might explain how dynamics happening at the interaction level connect to challenges understood at the organizational level—namely resistance and culture problems. This is why the interview and survey protocol was designed to probe for responses that reflected interaction-level dynamics, as opposed to general difficulties with change.

Some may challenge the idea that by searching for underlying reasons for difficulties of change, a proverbial ‘cure’ for change then exists. A panacea for change was not the objective of this methodology. While it is true that the goal of a new theory is to better explain a phenomenon, it does not necessarily follow that an improved explanation brings with it the end-all-be-all solution. Rather, the objective of the analysis was to improve the ability to diagnose why data-driven change is difficult.
CHAPTER 4

Analysis

The objective of this chapter is to provide a detailed summary of the major findings from the data collection consistent with the methodology described in the previous chapter. A majority of the analysis focuses on the qualitative analysis, which is the priority strand of research. The interview data and analysis take up the bulk of the chapter culminating in the development of the model of unintended deviation (MUD). The embedded quantitative instrument takes up a smaller portion of the chapter and culminates in the validation of the analytic facilitation (AF) construct. The chapter concludes with a discussion on the merged results that show how MUD, AB, and AF taken together, explain the difficulty of data-driven change at the micro and macroscopic level in ways imperceptible via traditional organizational charts.

Interview Data and Analysis

The interview collection period lasted from June 15, 2018 to July 15, 2018. Altogether, 25 subjects were interviewed. The inclusion criteria required subjects to have had worked in a leadership role in the hospitality gaming or related field for at least five years. 24 interviews were performed in person in Las Vegas, while one was conducted over the phone. Subjects represented leadership roles in hotel, gaming, analytics, marketing, finance, accounting, investor relations, consulting, and development. With respect to job title, the sample included managers, directors, vice presidents and C-level leaders. The firms these professionals worked for spanned from local market casinos, regional operators, and destination properties. Asset classes represented included local taverns all the way up to five-star luxury resorts. Line-level leaders, property level leadership, as well as corporate leadership were represented in the sample. While no demographic data was collected, the sample can be described as primarily male. Several females were recruited into the sample and two of them participated. The remaining twenty-three were male.

The initial stage of analysis was the process of breaking down the data into distinct units of meaning by describing what was happening in the data (Goulding, 2002). Within this stage, the
first step was to perform a line-by-line analysis of the transcribed data. Using written index cards, codes were named and renamed at the top of the card and quotations from the interview transcripts were written down with reference to the interviewee and the transcription line number. After the initial line-by-line analysis, 30 themes were discovered in the data. These themes were grouped into various categorization schemes. Through constant comparison and analysis of overlapping categories, one consistent pattern that arose was a bifurcation between effective and ineffective analytics.

**Open Coding: Effective versus Ineffective**

The broadest confirmatory finding from the interview data consistent with the literature was that data-driven change was challenging. It was immediately clear that there were frustrations experienced in achieving data-driven change. Managers were vocal and had many opinions about their frustrations with data-driven change. They freely expressed their ideas on what an ideal data-driven situation would look like. Despite the desire for change, there was consensus that the industry had not yet achieved the data-driven change originally sought. All interviewees had responses that called attention to both a simplified ideal and a complicated reality—in other words, what a data-driven world should look like versus what it actually does look like. This pointed to the understanding that potential fixes were out there but implementation of those fixes and adoption was difficult to achieve for various reasons.

This contrast between ideal and realistic also arose from a modification to an interview question. The opening question of the interview was, “what are skills that describe an effective analyst?” Early in the data collection, one of the respondents described the qualities of an ineffective analyst—“an effective analyst is...an ineffective analyst is...” This question was then added to the protocol as a probe question in all subsequent interviews. This elicited a much thicker description of the qualities and comparisons between effective and ineffective analysts.
Analytic Function

One of the early categories that arose from the broader theme of frustration was confusion over what the function of analytics should be within an organization, and correspondingly, how resources should be deployed in and around the analytic function. This was exemplified in Kevin’s quote:

“How many instances are there where the chief information officer (CIO) is trying to talk to the CFO or CEO about some risk that’s out there...and he [CIO] wants to spend forty million dollars for some system, and unless you can explain to that operating executive or finance executive, exactly what it does, they’re going to say no every time.”

Without understanding what is important, at least in this case, strategic direction and investments can be mismatched. Without a strong understanding of the analytic function, the role of the analyst or the analyst function can then get obscured. As Arthur discussed what can often happen in industry, “so somebody’s job is to look out for their boss. And so, an old boss of mine used to have a phrase, ‘what interests my boss fascinates me,’ so his job was to make his boss happy, if building this report makes him happy, then that’s what someone will do.”

These data demonstrated frustration and confusion in the analytic function, which was part of the ineffectiveness. Conversely, there were sentiments expressed on what a more ideal and well-defined analytic function should look like; what effective means. There were two subjects that voiced that all managers, even those outside of analytics, should have some basic analytic capabilities; in this vein, all managers have a duty to interpret data so as to justify business decisions to their superiors.

Through reflexivity, it became apparent at this stage of coding that the interview question of what describes an effective analyst was not necessarily specific to those who hold job titles that contain the term ‘analyst’. Rather, it became apparent that being an effective ‘analyst’ per se is a matter of communicating analytic ideas in such a way that the receiver of the information can
comprehend. This more generic concept of sender-receiver opened up the theoretical boundaries originally set forth at the beginning of the study; that not just analysts that hold that job title play the role of analysts. For example, a slot manager may receive an analysis from the analytics department. However, the slot manager may choose to provide his or her own interpretations in a situation where he or she needs to justify the results of the business such as in a P&L (profit and loss) review. This idea also aligned with AB—a term that implies that within a data-driven network, there is a sender of analytic information and a receiver that holds some decision making power.

The ideal situation was described by interviewees whereby an analyst has critically looked at the data and provided a succinct narrative of what the data is revealing. Furthermore, an actionable summary recommendation has been provided drawn from the interpretation. Idealized views of the analytic function only appeared with respect to a few themes. It was greatly outweighed by themes related to the less desired yet more often occurring ineffectiveness of analytics.

Skills and Abilities

With significant confusion over the proper role and resource allocation for analytics, defining the appropriate skills for what makes an effective analyst also occurred frequently in the data. In addition to asking subjects about effective versus ineffective analysts, interviewees were also asked about the balance between the teaching and learning of specialized analytic knowledge between those tasked to communicate their expertise, to others whom do not have the same expertise. Nadine expressed:

“I honestly think that it depends on...somebody’s personality and what their actual intellectual level is, if they’re ready to go to another level and actually learn how to process their own analytics, as opposed to somebody that’s just like, ’oh well what? I have to use a computer?’...I guess you could say to a point, people could be teachable, just given the right circumstances. It depends on what level you start at to
teach that...some people you need to start at the basics, some people have enough
knowledge to be able to kind of just dabble right into a report.”

This quote from Nadine showed that there were varied technical abilities from person to
person and therefore, communicating analytic ideas effectively would require different
approaches depending on any number of situations. It would seem that confusion was an easy
place to end up if the personality and intellectual level are not factored for correctly by the
presenter. This kind of mismatch contributed to another theme that arose in open coding, which
was ‘paralysis by analysis’. Referring back to Fiol and Huff (1992), this is a situation where too
much analysis leads to only marginal gains in decision making ability.

Paradoxically, when describing the effective analyst, many identified the skill of
questioning the data and looking deeper. This concept of depth being essential to effective
analytics was alluded to by more than a handful of interviewees. Both analysis paralysis and
depth of analysis implied the notion of taking time to look at something more closely. However,
the former concept is an unfavorable situation and alluded to a state of confusion, whereas the
latter is considered a desirable situation and alluded to a state of extended critical thinking.

As opposed to paralysis by analysis, the intended and more desirable analytic skill was
critical thinking. This was expressed in a multitude of ways including understanding why data is a
certain way. This theme reflected that some receivers of analytics did not respond well to
historical reporting referred to as “bean counters,” which was described by Kevin. An effective
analyst was described often as someone who questions the data and asks deeper questions about
why certain figures or calculations are expressed in a certain way.

Effective analytics was also described as performing more hypothesis testing, often
described in the interviews as ‘A|B’ or ‘test-and-control’. These terms alluded to the
implementation of the scientific method in the business world whereby tests are performed and a
null hypothesis represents that an experimental treatment has no effect and sufficient statistical
significance would be required to reject the null hypothesis and accept the alternative hypothesis.
Instead, what was described as occurring in industry were more quasi-analyses often driven by
intuition and anecdotes whereby the conclusion has been drawn prior to the analysis performed. The matter is considered settled once data has shown an analytic requestor’s anecdotal theories, whether they are statistically significant or not.

With a lack of critical thinking, an unclear understanding of the analytic function, and too many analysts assigned to reporting, another theme that arose was over-reporting. One of the interview probe questions asked if there was too much data out there. Many agreed with the statement, with the exception of one who clarified the question by making a distinction between ‘data’ and ‘reporting’. This sentiment aligned with the literature which expressed that a single point of data by itself has no value unless it is placed into context (Ackoff, 1989).

Arthur expressed the following: “There’s not enough data, there’s too many reports”, there was a considerable amount of frustration voiced as to the amount of reporting that was produced in the industry today. Arthur expressed,

“let’s imagine...you craft this really amazing report, and it’s well thought out, and it really teases the bubbles to the top, the important things. What your users are going to do is ask questions. It’s the nature of the user to do that. Your response is to build another report, and then another, and another...in the end, because of all the questions that folks had, there’s fifty reports. And I don’t know how you escape that.”

In a similar sentiment, Kevin expressed that, “you have a CFO, or a CEO for that matter, that doesn’t care about the analytics, and they just use it [analytics] as a report runner.“ All that is asked of these report runners are to produce numbers “last month versus this month”. Kevin said that “there’s a lot of people that have that job right now...there’s a bazillion of them.”

Outcomes

The themes of frustration and confusion demonstrated that the interviewees had far more to say about ineffective analytics versus effective analytics. In addition to asking about effective versus ineffective analysts, another question asked the subject if and how data is used more effectively in some conversations than in others. Darnell was quick to point out, “I would twist
that and not say ‘used effectively’, but say ‘used properly,’ because I think that’s a more fundamental basis: is data used correctly?’” Darnell made a key distinction between the effectiveness and the appropriateness of the analytics. This distinction was discussed in subsequent interviews. Interviewees agreed that the successful adoption of an analytic recommendation was not so much about the technique that was applied in the analysis, but rather and sometimes even more so, boiled down to the salesmanship.

Another question was asked about how data was used (and misused) in business. Many agreed that poor analytics delivered in an effective way could get adopted and conversely, great analytics delivered in the wrong manner could create adoption issues. By recognizing this distinction, the desired outcome of objective results originating from the scientific method and hypothesis testing was not what often occurred in industry, even though many would agree it should. Rather, subjective conclusions can often arise. For example, Mark said:

“Advertising becomes a little subjective when we try to put objectivity around it, but there’s definitely less data-driven decision making there at times than there could be. Some of that’s changing with more and more evolution towards digital marketing and areas we can measure...even in that world, there’s attribution models that, you know, that there’s some subjectivity to what actually caused that last click, you know along the way, that food chain is there. So even, in digital where you do have some data around it, there’s still, some subjectivity that comes into play. But you know, and a lot of it comes down to the leader.”

An extension of the salesmanship theme that came up in the data was the aesthetic of the analytic deliverable. Some of the interviewees expressed that the interpretations of the data may not resonate with certain stakeholders unless the deliverable looks a certain way. Unless data visualization and presentation tools have been utilized in the analytic deliverable, the interpretation and recommendations may not be as salient. This was a unique theme in the interview data in that there appeared to be varying degrees of priority placed on the visual look of
the analytic. Some leaders may appreciate visualization, whereas others may not necessarily find much value added in aesthetic considerations in analytic presentation.

Assessing statistical causality to financial performance with respect to other functional areas of a casino seemed to introduce a level of subjectivity. In a hospitality gaming setting with various revenue generating departments, themes of blame and mistrust also arose as an outcome of subjective interpretation. Bob noted that,

“If you’re looking at F&B off of something, and they say, ‘no it’s these guys are blaming it’ or whatever else, and then you look at the numbers and go, data doesn’t lie. So that’s why you have to bring everybody to the room, bring all the liars to the table and then say, here’s what works.”

This expression of lying under the broader themes of confusion and frustration show that analytics, despite a seemingly inherent objectivity, can be used as a form of manipulation. This in turn was said to lead to trust issues. “people are trusting you’re reading the data properly” said Darnell. However, it appeared that confusion over the role of analytics, paired with the associated bureaucratic challenges, made objectivity and trust in the decision making process the exception, and not the preferred norm.

By the end of the open coding process, it became clear that there was a difference between how the data-driven organization should look like compared to what it often turned out to be. While some examples of successful data-driven initiatives were provided, the data was dominated by the challenging side of data-driven change.

**Axial Coding: Unintended Deviation**

After open coding, which included a line-by-line analysis identifying 33 codes and three categories, axial coding was performed. In this stage, codes and categories in the open coding process were recoded based on subcodes that connected the categories to each other in such a way that provided a more fuller picture of the challenges of data-driven change. This was performed in line with the research questions and to inform the emergent theory.
Confusion and frustration were the broader themes in the first stage of coding, which arose from the rift between describing effective and ineffective analytics. Confusion was evident with respect to the appropriate role of analytics, the necessary skills to be effective in analytics, and the subjective outcomes that arise despite the idealized desire for objective conclusions.

Through constant comparison of themes and subcodes, an axial code of deviation was settled upon. By using deviation as an axial code, this implied that there was both an intended destination towards desired data-driven change, as well as a path that led elsewhere. One path reflected the intended ideals of data-driven change; or effective analytics. On the other, was a path that the organization did not originally set out for; or ineffective analytics.

Despite an understanding and a desire for data-driven decision making, at some point along the path towards the idealized destination, something somewhere went astray. One of the categories created in the open coding process addressed the notion that analytics can create more questions than answers—confusion and frustration arose as managers talked about various pain points. Instead of providing clarity, analytics could instead produce a more convoluted view of what was going on—a deviation was theorized to be occurring.

Readers may contend that just because effective and ineffective analytics can be distinguished, it does not necessarily follow that a deviation is occurring or that a path towards ideal analytics exists—discrete opposite concepts do not imply deviating paths. To this counterargument, deviation did not directly appear in the data. The concept arose through constant comparison of various axial coding schemes. Arriving at the axial code of deviation was a result of first contemplating diversity as a possible axial code—in the end, diversity was determined to be a subcode that informed the eventual axial code of deviation.

Diversity in this context referred to a wide array of situations that managers and analysts found themselves in. Prior to arriving at the deviation axial code, it was initially surmised that diversity was what made data-driven change challenging. It seemed reasonable to assert that knowing how to effectively communicate to stakeholders across a complex business was a tall order for anyone. Furthermore, there was a diversity of roles and functions that was not only
apparent in what was discussed in the interview data, but also across the diversity of interviewees themselves and the roles and functions in which they represented.

While it came as no surprise that hospitality gaming is often characterized as a diverse workforce, it seemed that the ability to skillfully navigate diversity required social skills that were not necessarily inherent to what is typically associated with analytic talent. This was in contrast to the social skills generally associated to more customer-facing service roles. While it was common to identify that communication skills were important for effective analysts, it remained unresolved if the content of that communication mattered in its objectivity—as the data showed in open coding, for some, simply pleasing the boss means doing your job well.

The concept of being skillful as a communicator in a diverse environment was independent of whether or not an analytic deliverable was designed to please the receiver (subjective yet effective), or whether the analysis was appropriately performed; statistical objectivity did not imply effectiveness. This gap between objectivity and subjectivity, in spite of the need to communicate effectively amid diversity seemed as if it was never intended. This led to the notion that a deviation was occurring at some point. If objectivity was always the ideal, then arriving at subjectivity was an unintended deviation.

This axial coding section was written to describe how the subcode of diversity transitioned into the axial code of deviation. In doing so, data are first presented to describe the subcode of diversity. Of focus was the interplay between diversity and the corresponding need for communication skills.

Through the axial coding process, the reflective question arose whether or not a strong analyst from a technical and procedural standpoint could thrive in the industry without ever having developed communication skills. In other words, did the difficulty of data-driven change make communication skills a requisite for effective analytics, or did this need exist prior to the situation being difficult?
Stakeholder and Situational Diversity

Analysts have to navigate through a myriad of stakeholders. David pointed out when recruiting analysts, “we tend to be more forgiving than we should be when it comes to communication skills.” In the operations realm, those managers “should naturally be a little bit better in terms of communication, because they have a lot more variant people they deal with...people all day every day.” This distinction implied that there was a difference between what analysts and operations staff are exposed to, which informed the way the respective camps look at their businesses. Even within just the corporate ranks, communication can be “tricky...because you have so many different types of people...one GM love data and wants to look at it, and one doesn’t care pretty much at all...and is more big picture [on] how the overall business doing.” Numerous interviewees pointed out that gaming draws a wide range of people who have to figure out ways to work with each other. “You can’t expect everyone to be good at everything,” noted Cody.

The diversity of stakeholders brought with it a diversity of interaction situations. It seemed very difficult to be able to anticipate the proper communication necessary for every situation. Within the broader theme of confusion, the data began to reveal that situational diversity was contributing to the confusion because the multitude of situations required different communicative approaches. “I can tell you within our organization, every department is different because when I go into meetings, going into those meetings, I know how they’re going to be based on the management in that area and what their strengths are.” Bryce expressed that “analysts sometimes can confuse some non-analytical people. I think they’ll nod their head, and kind of like they know what’s going on, but they have no idea what’s happening, and then they have no idea how to act on it.” On the point of some reports, “they’re pretty, and they look good, or they look bad, but nobody knows why they look bad or why they look good right?” From a corporate perspective communicating with property level managers, Roland expressed that, “I don’t think they [operations managers] really understand as much as they think they understand...and I think people sort of pretend like they understand or they say ‘sure’.”
Need for Soft Skills

Studies such as Robles (2012) and Heckman and Kautz (2012) have shown that soft skills are important in today’s workforce where a diversity of interactional situations with varied stakeholders arise. Hospitality gaming is one such environment. To this point, one of the most readily apparent and commonly occurring theme in the data was the need for soft skills, which is a distinction from the hard technical skills that are generally associated with analytical talent. For many interviewees, being an effective analyst required more than just the ability to ‘crunch numbers’, but in addition to this, being able to communicate said numbers effectively. This was expressed in a multitude of forms including ‘summarization’, ‘distillation’, and ‘translation’.

Some interviewees noted a caveat to the argument that all effective analysts should possess soft skills. Some drew a distinction between the skills of an analyst and that of a leader of analysts. When asked about the need for soft skills such as understanding the audience and salesmanship, Darnell responded with, “I think that’s part of being an effective analyst manager. I don’t think the analyst themselves need to be able to do that.” Similarly, Ross expressed that, “I think it’s more on the junior person to kind of present the senior person an easy way to look at things and kind of walk them through and explain it.” This distinction seemed to stem from the notion that skills varied across analytic teams and that simply having an entire team of well rounded individuals with an ideal balance of soft and hard skills was unrealistic. Rather, high-functioning analytic teams were better served identifying those that skew toward a stronger hard technical skill set assigning them to more quantitatively oriented tasks, where leaders of analytics should be more inclined to engage in relationship building outside of the analytics team.

It was reported to require a mix of soft and hard skills to build a well-rounded analytic function, either at the individual or group level. Also, it was argued that not all analysts are fit to lead analytics. Taking these points together, interviewees would agree that the search for leadership talent is not always easy. To this, Darnell said that, “there’s a very small breed of people that have those soft skills and the strong analytic skills because those are typically diverting paths.” Opinions also varied as to what degree those skills were teachable. One
interviewee suggested that having those soft skills were innate to the person.” Another interviewee suggested that developing those skills only comes with experience. Regardless of the nature-nurture debate on analytical soft-skills, it became apparent that within the analytic function of an organization, different skills were required and that the concept of an effective analyst is relative to the skills and role of that individual.

**Effective communication of analytics.** Within the soft skills theme, the more specific skill of being able to effectively communicate analytics was identified. This need for translation arose from both situational differences in interactions as well as having to work with a diverse range of personalities. This pointed to the idea that analytics were not simply deliverables of pure data substance, but rather, involved stylistic and tactful considerations. This was indicated by interviewees mentioning factors including tone of voice, choice of forum and venue, as well as the level of respect that the sender had for the receiver of the analytic. These considerations also solidified the AB construct.

**Sender misjudgments.** To this sender-receiver dynamic, one of the most commonly occurring themes was knowing your audience, which was described in a variety of ways as an error on the part of the analytic sender. One situation involved the sender of the analytic as not being respectful enough to the receiver. This was expressed in a couple ways. The receiver may have felt that their work experience was not being respected and that the sender of the analytic was being pompous. Another dynamic was that the sender provided a recommendation that may have embarrassed the receiver in front of his or her team in such a way that the receiver felt ridiculed. Patrick expressed the following:

> “Some people that are in leadership positions will not take well to someone trying to teach them. Others will say, ‘this guy’s really trying to help me, and he doesn’t want to make me look bad in front of the group, so he met me on the side, he talked to me like a human, and he tried to help me,’ versus, he brought it up in the meeting in front of God and everybody, and that made me look bad…”

This pointed to a lack of attention to understanding the right forum to show an analysis,
where an audience member may be adversely affected by the conclusions. The next two excerpts described the need for sensitivity of delivering analytical findings that may not be in line with what the requester was originally looking for. Cody provided a similar sentiment:

“Get [the audience] what they want as a deliverable and then add some other, you know, items on top to say, ‘hey, I noticed this, this, and this. I don’t know if that really would affect you in any way or you’d be interested in seeing this, but I wanted to at least bring it up to you so you’re aware.’ So that’s one thing I’ve learned...give them what they’re asking for first and then the other items that you notice afterwards.”

Alice provided a detailed explanation of this concept by saying:

“As part of [BEING AN ANALYST], if you’re told [TO FIND DATA TO SUPPORT AN INITIATIVE OR A DECISION], of course you should provide that support and fulfill your job. However, you will not do justice to yourself or to the decision making process if you don’t seek and propose alternatives. So, in my opinion, an analyst needs to provide the individual with exactly what they requested, which starts the conversation in a positive manner; then, present alternatives, even if alternatives are against the original line of reasoning.”

Striking the right tone was also indicated as important to the effective delivery of analytics. Arthur said “it’s our job to convince them, not scream at them.”

To this same point, Alice expressed:

“the analyst must help develop that [data driven/analytical] mentality in individuals and across the organization. [THE APPROACH SHOULD BE NATURAL]. The analyst should gauge the perception of the individuals, and modify the approach accordingly. Little by little, as the analyst gains trust, those who [DID NOT EXHIBIT THIS DATA DRIVEN MENTALITY] previously will see its value to the overall decision making [PROCESS].”
Other situations of ineffectiveness included having data presented in such a way that did not include sufficient summarization and recommendation. This was often met with a reaction of disbelief. This was expressed with quotes such as, “[they] just hand you a report” or this “whiz-bang thing.. what the heck... what do I do with this?”

Also considered ineffective was a lack of validation or inspection of the data on the part of the sender. This occurred when an analyst simply produced a report without actually looking for peculiar variances or outliers that were subsequently found by the receiver of the analytic.

**Receiver misjudgments.** Even with the right delivery on the part of the sender, there was no guarantee that the receiver of the analytic was effectively receiving the message. One of the more commonly occurring themes in this category was the oversimplification of analytical and technical concepts. Certain interviewees, who were in roles closer to the technology and infrastructure related to data solutions expressed that often, other leaders too easily get frustrated and demand that systems simply should work, not realizing the labor and processes required to process the immense amounts of data as well as ensure the cleanliness and quality of the data. In discussing the complexities of implementing data systems, Cody said:

“...then trying to find out, ‘do you have the software and the applications to provide that’ in [a certain] mannerism and if not, it’s time to start researching and finding out what’s available, [and] what’s the training background that’s necessary for it, what’s the cost of it, can it be shared among other people, is it integratable to any of your current applications that you currently have? Because that’s a big problem too, if it’s not, some things aren’t, you can’t integrate them in. You have to, you know, take data and manually input into the servers or other items. It can get very laborious...so you’re taking good time away from when you actually should be looking at data, and instead you’re just trying to get the data to where it’s useable. So that could be an issue as well.”

Armando expressed a related sentiment about how specialized knowledge gets misunderstood because there are too few individuals who comprehend the technical details
involved in data systems.

“I think a lot of casinos get to that point where you have one point of failure where it’s like this guy’s the guru of everything...I think it needs to be a knowledge [base] that we can all use it. Yes, you still probably have to have some super-users, but should that person leave, you have the support of the company who you bought [the technology solution] from...multiple times I’ve seen where it’s like if this person is gone tomorrow, business shuts down.”

Misjudgments in communicating analytics effectively occurred with respect to both the sender or receiver. Soft skills were addressed as necessary for effective communications. To this point, it seemed that for facilitation of analytics between sender and receiver to be successful, a mutual compatibility of style, respect, and understanding was necessary.

**Presence of Biases**

If the sender and receiver of an analytic are compatible from a communications and soft skills perspective, this does not also imply that the analytic was performed properly. There still exists the potential for providing analytic deliverables that do not pass the standards of statistical validity. Improper data and or conclusions from weak inference can still be communicated effectively between network nodes.

The presence of biases in analytic interactions was a prominent theme in the interview data. Particularly with respect to responses provided on the interview question on data being misused in conversations and interactions. Its frequent occurrence led to the understanding that biases played a certain role in data-driven change. Exactly what kind of role was difficult to pinpoint during the open coding stage of analysis. Part of that was because of the challenges in defining the nature of data itself.

The term ‘data’ was for some interviewees, described as an objective artifact of information, immune to any biases. Data however was also described as something that can be manipulated to draw different conclusions. This paradoxical conceptualization of data was
summarized by Bob who expressed, “data is key in everything and data should drive every
discussion...it’s the fabric that makes everything work because the numbers don’t lie”. However,
Bob also stated that, “you can manipulate it and try to get it to any way you want it to, but if you
show this is not going to pencil out any way, shape, or form, it’s hard to put lipstick on that pig...”
Kevin echoed with respect to trending data, “you can spin data to mean anything you want
to...pick a metric, and it goes up for a good reason, or it goes down for a good reason. So I think
it’s spin-able.” Bob also noted that assigning causality is a murky exercise in that it’s “hard to say,
well this is what’s driving this [number].”

Understanding the role biases played in the broader context of change was unclear but also
important and warranted close examination. It was easily understood that having biases present
could lead to wrong conclusions or improper recommendations. If the ideal of data-driven change
is statistically objective decision making, this would be ineffective. The assumption here is that
no business is intentionally seeking wrong analytics, albeit some firms such as Enron have gotten
themselves in trouble for doing exactly that. Despite their unfavorable nature, biases were
discussed in various ways throughout the data.

Skip made the point that in the absence of looking at the overall financial picture, certain
areas of a casino result may focus exclusively on the interests of their own area, and this can lead
to biases entering the picture.

“I would argue that it’s the analyst who has to take a much more holistic approach
and say look, even though you, Mr. ‘race & sports book director’ is losing a little bit
of money, I can see that football contest that’s costing you this and making your
numbers kind of suck is doing much better. Slots is doing much better because of the
increased foot traffic. You know. Race & sports director is going to look at you, he’s
going to say look I’m not getting the business in my race & sports book to justify this.
This is stupid. I’m going to cancel this contest. Yep. You’re right. Except the casino
might suffer. Ok? And it’s the analyst who has to come back to the decision maker
and say, hold on, wait a minute. Let me show you what’s really going on here.”
**Confirmation and selection biases.** Nadine suggested that individuals may gravitate towards a certain perspective on the business:

“I’ve found that people could be opinionated and think that, well this is how I think, and this is how it should be analyzed, so they’re not necessarily looking at both sides of the picture...they’re just looking at the side that they empathize with.”

Dan alluded to the concept of a narrative that arises from the data and that selection bias can enter the picture to feed a specific narrative for purposes that may not be performed for the purpose of achieving statistical validity:

“You can use the wrong process. You can still interpret information to tell the story that you want by highlighting particular elements of it and not [SHOWING THE WHOLE PICTURE]. There’s definitely a way to do that whether it’s overt or more covert.”

In a separate excerpt from the interview, Dan said:

“You can manipulate [THE STORY] with the absence of certain elements of information to tell a story, and that’s where organizations either need to have independent analytical departments and/or have a culture where you can challenge each other in a meaningful way, and to come to the best outcome.”

Selection bias can also take shape in relation to statistical techniques. Dominic pointed out the following:

“I’ve seen too often, a simple application, just put a bunch of variables and run a regression on them...without thinking what is the operational way things work. Sometimes, there’s a structure to the relationship between variables if you just think about it.”
Dominic’s description shows that analysts may sometimes take a haphazard approach to variable selection in developing a significant model, which may not be grounded on a strong theoretical basis. This could lead to the development of drawing spurious correlations and assigning a meaning where a true causal relationship may not necessarily exist.

**Correlation-causation.** The combination of different biases appeared to provide stakeholders a tantalizing reason to fall into the correlation-causation trap. Arthur expressed that managers will often engage in the following sequence of events: “You see a pattern. you come to a conclusion...you then tell your analyst, here’s my conclusion, go support it with numbers, and that is common.” Arthur discussed that the ability to recognize patterns in data, while useful as a means for interpretation, is also one of the most abused forms of reading data output. Rory showed that a correlation will be drawn even with limited data that in this example combines selection bias and the correlation-causation trap.

“They had done an event and done some post-event analytics and were talking about how great it was and, you know, the event did this, and... just one piece of it was like a survey they did of the people who attended the event...I said ‘how many respondents did you get?’ and it’s like ten and I said that don’t really tell you anything.”

By sorting out the different kinds of biases that arose in the data, it started to emerge as a possibility that biases played a role in widening the deviation between effective and ineffective analytics—it certainly was not helping the cause. The interaction dynamics involving sender-receiver compatibility did not guarantee that sound analytics were being performed. A compatible relationship could still be wrought with biases as the analytic role could simply be utilized as a means to address the biased interests of the requestor.

However, if an analytic deliverable revealed a conclusion that would not be well-accepted by the receiver of the analytic, or it was delivered in a disrespectful way, then it could be that the analytics may be sound but not effectively communicated. For strategic decisions to be driven by appropriate, unbiased, objective analytics, the sender-receiver compatibility has to allow for
unpopular conclusions. In the absence of this, biases seemed to emerge as a way to rectify the incompatibility in communication.

To this point, the emergent model (Figure 3) indicated that some deviation was occurring with an idealized path reflecting effective appropriate analytics and a deviation from this ideal path where soft-skills compatibility was less than ideal, or that analytics was producing improper outcomes rooted in biased motives. Upon completion of axial coding, it was concluded that the deviation was enlarged by the presence of biases. This did not imply that biases were the initial cause of the deviation. Rather, some other factor started the deviation process, causing biases to arise. Furthermore, this deviation was never intended—miscommunication and biases were never the goal to begin with.

**Selective Coding: Impetus for Deviation**

At this point of coding, it was recognized that biases were present and were theorized to be fueling the deviation between effective and ineffective analytics. However, it remained unclear what was motivating stakeholders to introduce biases, even though there was consensus agreement that objective data-driven decisions were the preferred ideal. The emergent model was still missing a critical component; herein lay the selective coding process.

To review, selective coding is a process of integrating and refining the analysis and selecting one core category to form a larger theoretical scheme. A core category forms the focus around which all other categories and subcategories are connected by. The objective of selective coding is to explain the data via a core category (Locke, 2001).

Having a data-driven organization was an easy concept to buy into—“the numbers don’t lie” as Bob said. However, somewhere along the way, the gravitation towards being OK with biases tended to outweigh the aspiration for objective and appropriate analytics. The key emergent inquiry here was addressing why deviation was occurring in the first place. It was already established that data-driven change was considered desirable (McAfee & Brynjolfsson, 2012). The literature also noted that the challenge of achieving data-driven change was not for lack of top-management buy-in (Bean, 2017, April; Rothberg, 2017, June 26). With qualitative
Figure 3. Emergent theory after open and selective coding.
triangulation found on key stakeholders being committed to the ideals of data-driven change, why then did organizations seem to be drifting astray?

The section was written to walk the reader through the process of inductive reasoning beginning with disparate concepts of an incomplete theory and concluding at a point where key components of an emergent theory have been developed. The induction began with two foundational premises.

The first premise was that objective data-driven change was desirable as evidenced in literature. The second premise was that data-driven change while idealized, did not often go according as planned and deviated towards ineffective and subjective analytics as evidenced in the qualitative data. To the aims of selective coding in producing a core category, there seemed to be a missing link between what was desired and what actually resulted.

The first premise explained the goal of data-driven change, and the second premise explained the outcome. What was missing was the explanation of the process that led from the original goal to the unintended outcome. While the selective code of overprotectionism was ultimately determined, this did not arise immediately, but rather, as grounded theory methodology prescribes, through a multi-iterative process whereby data was systematically gathered and analyzed (Strauss & Corbin, 1994).

To review, the line-by-line analysis of the open coding process revealed frustration and confusion over the role of analytics—pleasing the boss did not always imply performing appropriate analytics. In axial coding, it was determined that pleasing the boss often meant producing analytics that appeased biased viewpoints. Somehow then, motivations at the interaction level between analyst and immediate supervisor translated to broader frustration and confusion at the organizational level. To this point, grounded theory methods are considered for examining linkages between interaction level dynamics and larger social processes (Charmaz & Belgrave, 2007).

The selective code had to therefore reflect a motivating factor for managers to go against their own ideals in wanting objective analytics, and instead tasking analysts with producing
results that aligned with their biased perspectives. This was not to suggest that managers are inherently biased or motivated to be biased. Instead, the assertion here was that managers feel justified in adopting biased analyses, whether they are aware of it or not. To this end, the selective coding process looked for clues in finding defensible reasons for selecting bias over objectivity.

Several selective codes were considered in explaining the entirety of the data. Early selective codes included tribalism and territorialism. These terms reflected the idea that business units were behaving in a way that did not represent a facilitative relationship required of sharing objective analytics across the organization to drive strategic decisions. Business units were forming ingroup and outgroup biases that favored their own interests over others. However, upon reflexivity and constant comparison of themes in relation to the network framework applied in this research, it was determined that these terms leaned towards an anthropological nature rather than organizational or business oriented terms.

Another selective code that was considered was fragmentation which achieved the goal of moving away from anthropological descriptors. Fragmentation was described in reflective memos as an unintended consequence of organizational design, namely departmentalization—which to a point made by Molina (2001), is a natural inclination for firms to want to separate their operations into functional areas or business units. However, upon continued reflexivity, fragmentation was set aside because it seemed too general as a theme. Also, after an exploration into extant literature on organizational fragmentation, the notion that organizations can be fragmented did not represent an incremental contribution in explaining why change is difficult. In other words, to say that change is difficult because organizations are fragmented seemed to be a re-explanation of the problem rather than a description of a causal relationship.

On the continued analysis to find the initial stimulus of bias formation, a more systematic reevaluation of the deviation theme was performed by plotting the deviation along a more temporal path. There was an understanding that deviation had to occur at some point in time after which the goal and the reality were once congruent. It seemed that the deviating reality and the intended reality occurred some time after the top-managers were bought in and before the
bias-driven analytics were performed, all of which were prior to the outcomes of the analytic interactions. The interactions were identified as a result of higher-level resource decisions, and those decisions were driven by leaders that must have been just below the very top-level managers.

The possibility arose that the deviation and the formation of biases started at a point between the very top of the organization and the management layer just below the top. However, this was determined as not descriptive enough. A stronger description was needed as to the root of the deviation.

**Source of Deviation**

It was decided that the core category would represent the unexplained link between top-management buy-in of data-driven change and the deviating paths that led to effective analytics and unintended ineffective analytics. A deviation that was fueled by the presence of biases—biases that on principle of data-driven analytics, should not exist.

The following quote from Bryce, a revenue management started to reveal that there was a disconnect between the desired vision and the resulting deliverable. The executive expressed that it is not uncommon for leaders to “put people [analysts] on a bunch of different things and we forget what we even asked,” and therefore “it [analytics] just comes back to us, it’s not acted upon”. Bryce also noted that requests for analytic departments can often be convoluted and more improvement is needed in providing analytic departments with a “concise ask...making sure we’re not just putting together graphs.”

In a similar vein, Cody expressed that often, casino special events are approved of without the proper data tracking mechanisms in place, which opens up the possibility to “draw conclusions that aren’t actually factual.” This alluded to the point that approvals to run events can sometimes supersede the desire to understand their performance correctly. This notion that leaders were making decisions that they either forgot as in Bryce’s case, or were not able to properly track as in Cody’s case, reflected a deficiency in resource deployment. Resource in this
context seemed to connect to the established definition of resources as all assets, capabilities, processes, information, and knowledge that is under the firm’s control (Daft, 2012). However, without clear direction of what the analysts should do or track, the analytic resource utilization as described by Bryce and Cody was less than ideal.

While there may be clearly defined roles for analysts as they relate to formal job descriptions, the roles analysts played in actuality did not always reflect the optimal utilization of human resources. Several interviewees expressed that analysts sometimes are underserved and used for the development and distribution of reports, of which these reports have arguably little value. This was expressed in contrast from the desire for actionable intelligence whereby the receiver of the analytic walks away with an understanding of what he or she needs to do based on the information provided. Some of the frustrations expressed in this area reflect that in some cases, analysts are grossly underutilized to create more reporting than is required. On reporting roles, Rory expressed that:

“I would speculate that in my experience, that has been more than 50 percent of the time...they’re not really generating insights. They’re just generating historical reports, and they’re leaving it up to you or to whoever gets the reports to generate their own insights, which I think really leaves a lot off the table.

Similar to Bryce’s expression that managers sometimes “forget what we’ve even asked” of analysts, Rory’s notion that things are left on the table reflected that resource decisions were made, with little recognition of if those resources were used in an optimal way. This also reflected in some ways, a disconnect in understanding technology. To this point, it was discussed in open coding, how receivers of analytics can underestimate the complexity of data technology and relegate systems to the overgeneralized notion that they simply should work as designed. The following quote from Stephen addressed this same point by also saying that the industry can be a revolving door for technical professionals whom reported to leaders that misunderstood the specialized manpower required in data systems integration:
“There’s not enough people that know how to actually run the tool effectively because companies will invest in this tool and think, ‘oh it’s just going to run itself,’ but you have to have the administrative staff, the people that make it work. It’s not, we’re going to spend a million dollars on whatever analytic tool, SAS, SPSS, Tableau, even Terradata... You have to have the right people, the right processes, and you have to invest in people. Otherwise, it’s not going to be successful, and it’s happened time and time again on The Strip [Las Vegas] where companies invest in something, and it fails, and they rip it out. That whole management team gets fired. They bring in the next guy. They bring in their buddies, and they bring in a new product. And, you know, there are stories up and down The Strip where that’s happened multiple times.”

Misjudgments in underestimating the ease at which analytics should happen, combined with the sentiments that analytic directives can be given with little oversight led to a situation where stakeholders making large resource decisions became impatient with the results of their data-driven ideals. Two of the resultant consequences were that more resources were used on historic reporting than desired as well as high employee turnover with regard to technical roles. Both of these results reflected below optimal analytic resource utilization.

At this point, it was recognized that data-driven resource utilization was less than ideal, and top-management although bought into the idea of data-driven analytics, were frustrated and perhaps even impatient with the results. Based on the revolving door of analytic talent described by Stephen, a hypothesized scenario was contemplated. If the technical data support talent was perfectly competent, would desired data-driven change be achieved? Was this the only thing holding it back? The answer to this was no because it was determined earlier that the analysts tasked with interpreting the data still may not be capable of employing the right soft skills to deliver unpopular (yet appropriate) analytic findings effectively.

It appeared at this point that there was a disconnect that top-management, while bought into data-driven change, did not quite understand what this completely entailed. Top-management was well intended in pushing for data-driven change, but somewhere after that point, those same
leaders became impatient with the lagging results of their own data resource decisions. This contemplation was not expressed to assign blame to top management or to data professionals. Rather, the point of this reasoning was to better identify the location where deviation was theorized to be occurring: just below the top management layer. As to why the deviation was occurring here was a different story.

**Reason for Deviation**

Confusion was evident around roles, resources, and leadership of data-driven change. This seemed to be exacerbated when organizations became larger and more complex. Bob expressed that when firms scale upwards, so too follows the bureaucratic challenge. This view was shared by Abe who noted that by having more and more departments, data-driven change has to be something addressed vertical by vertical. The theorized deviation between effective and ineffective analytics was not only a challenge that was occurring between an analytic sender and a receiver, but also with respect to the broader organizational structure. This suggested that something in organizational design may play some role in the deviation.

In the open-coding phase, it was revealed that there was confusion surrounding the role of analytics. It was discussed that the job of the analyst could sometimes mean simply performing what their immediate supervisor is requesting. This included building reports and satisfying requests that were not necessarily pushing the boundaries of analysis within the organization. The selective coding phase, the same theme of confusion around the analytic function was addressed with respect to how it was housed within the organizational structure. Within this realm, two reflective questions arose. The question focused as to what degree analytics should be centralized or decentralized. The other question focused around the concept of organizational silos and what role analytics plays in working across the different functional areas of an organization.

Abe expressed that the analytic function remains poorly defined within larger organizations. “I think organizationally, things have to change where analytics probably needs to be a little bit more centralized so that different pieces of the organizations don’t have their own analytics
group, kind of like shadow analytics groups...” This shadow term in some way implied that areas were not being completely transparent, and that trust issues were at play.

Earlier in axial coding, the presence of biases was described raising the idea that data can be manipulated to express a particular narrative. As it relates to the centralization of analytics, Dan expressed that, “it’s a real tough balance in terms of having distributed analytics versus more dedicated resources within a function...there are trade offs so ensuring that there’s a degree of independence I think is certainly important.” Kevin echoed this sentiment by saying that “to use data effectively, you need multiple perspectives...I would not base an operating decision on one metric. There has to be, you know, a triangulation guy.”

It seemed that objectivity and validity were worthwhile goals. However to this point, the degree to which a data enforcement role was formalized and centralized within an organization, particularly a large one, remained a challenge to data-driven change. There was a paradoxical dynamic of analytical oneness per se in that ‘independence’ implied the favorable concept of creating validity and objectivity, but ‘siloing’ implied the unfavorable possibility of covert motives occurring thereby creating mistrust in the organization.

The related concept of competition also subtly arose in the data as a consequence of siloing. On this topic, Dwight expressed that:

“Yeah, [it] really creates within an organization a competition for the same resources, when in reality you should be aligned to do, you know, the same thing, as opposed to, you know, competing for just inter-company charges, right?...We’re gaining nothing as an operation by moving money between gaming and hotel if there’s no real even impact, so at what point...are you making the right financial decisions or not in total, as opposed to each. We run into a lot of, ‘I want to build this department for that’, well, you know...all we’re doing is keeping job security for the accountants so they can move all the money around...you’ve got to be careful with that because it is (important), but it’s still very important to know if your rooms are making money or if your gaming works... there’s a balance there between what’s enough
This concept of competition was distinct from the blaming described in the open-coding phase. Blaming and mistrust were themes that related to the outcome behaviors of ineffective analytics. By contrast, the competition pointed out here was more reflective of the idea that the motivations for departmentalization can be misguided, even if there are justifiable intentions such as creating departmental accountability. This did not always go according to plan however. Rory expressed that:

“You have analytics that are trying to help you get your insights that can help guide your change, and if that analyst...co-shares that vision of where you’re going to go, I don’t mean they help create it, but they certainly understand it, right? We’re trying to do X, you know, and ok, now I see what you’re trying to do, so is your analytics supporting that, or is it just, you know am I giving a grade for how you did for the last quarter?”

Emergent Theory

Comments from Rory and Dwight reflected that the formation of departments, the way in which departments were ‘graded’, and the idea that ‘job security’ issues were at stake, pointed to the concept of survivalism. Amid a competition of resources across departments, coupled with the exercise of departmentalization, an evaluation process seemed to arise whereby a poor grade may lead to less job security.

The purpose of the selective coding process was to connect the deviation theme found in open coding to the top-management buy-in grounded in literature. To get a complete picture of this missing link, both the source as well as the reason for why deviation occurs was examined. The impetus it seemed was located at the resource and departmental decision making level.

The reason for the deviation, albeit unintended, was to ensure that departmental performance was operating at an acceptable level creating accountability. Although biases were
considered undesirable for data-driven decisions, employing biases as a means of justifying financial performance may become perceived as necessary for departmental survival. A theory was starting to emerge whereby deviation was accelerated by biases, but these biases were not themselves, the root cause of the initial deviation.

Instead, the suggestion was that resource and departmentalization decisions were the starting point of deviation. Decisions made at this level seemed to create unintended ramifications. This included creating a motivation for stakeholders to latch on to biased analyses to protect their own survival. This seemed to happen even in spite of having organizational buy-in on adopting data-driven ideals.

Model of Unintended Deviation (MUD)

Top management buy-in for data-driven change is supported in literature. Frustrations and confusion arising from the unintended consequences of Big Data is supported by both literature and interview data. Taken together, the supporting data framed the complete theory advanced in this dissertation, which is described as the model of unintended deviation or MUD. With deviating paths rooted in a singular starting point as well as a point of deviation identified, a complete theoretical model emerged. Arriving at this selective code was not done without reflexivity around other possible selective codes and through constant comparison of established codes, literature review, and entirety of the qualitative data.

Figure 4 illustrates that from an intended destination of data-driven change where analytics are effective (and appropriate), the actual path can deviate away from the ideal path following an unintended path where analytic resources become ineffectively utilized. The unintended deviation is caused by survivalistic overprotectionism—the selective code of the qualitative data. Protectionism by itself is considered to be a fair and worthy quality for managers to have, but specifically survivalistic overprotectionism represents the missing link—the impetus for the deviation causing ineffective analytics to arise.

At the beginning of the selective coding process, terms such as ‘tribalism’, ‘territorialism’, ‘survivalism’, and ‘fragmentation’ were considered. These terms were set aside as they either
Figure 4. Model of unintended deviation (MUD).
reflected too much of a departure from the organizational sciences or because they were too
general. As the theory began to emerge in selective coding through grounding in qualitative data
and literature, the term protectionism began to gain a foothold. It seemed that on a fundamental
level, it was reasonable that business units would ‘protect’ their functional areas in the case where
unfair criticism was levied on them with respect to performance. Available data and analytic
resources would be called upon by actors to developing interpretations that support a protectionist
narrative that one’s department was performing at a sufficient level.

This concept of protectionism seemed fair on its face but it could be challenged that this did
not completely align with the frustration and confusion that arose in open coding. In other words,
protectionism seemed like a good thing, whereas confusion and frustration were unfavorable.
However, within the frustration theme, cross-departmental blaming seemed to imply that
protecting one’s own interests may take shape even if it means harming another—in other words,
throwing someone else under the bus.

It could also be challenged that protectionism was a means of shielding one’s area from
unnecessary risk. The concept of risk and its relationship to change was mentioned in the data,
but not to an extent where it was considered a theme. From the literature, strategic thinking is
described as pursuing activities that differ from rival firms (Porter, 1996); it therefore involves
risk. Still, even in a hypothetical situation where analytics concluded that a risk was worth
pursuing, survivalism and protectionism may win out over sound statistical conclusions.

To this point, Ross stated that “gaming and hospitality has been very slow to embrace
change...there’s this thinking of this is how we’ve done it before.” Ross also considered that
where people are in their career may play a factor into this: “guys work their whole life to get to
the C suite, and now it’s like geez, I don’t know if I want to just go do something like totally new
or kind of just like ride this out five years, then call it quits, you know?” The incentive to not put
one’s career on the line may not be worthwhile even if the risk pencils out as a safe bet to make.
**Survivalistic Overprotectionism**

The concept of protecting one’s domain whether it be their department or their career seemed to be a fair and rightful way to behave. However, a distinction drawn was between general protectionism and overprotectionism. Protectionism as a standalone theme was a description of a management quality. Overprotectionism implied that managers may do more than necessary to protect the interests of their areas. This sentiment was captured in the following quote by Roland that showed that different leaders are fighting for their own areas more than they may care about the broader business:

“There everybody has their territory and they don’t like people that step on anybody’s toes. I had that when I was selling slot machines, and I was selling bar machines for the company, and you go in and you want to rip out a bar and put a new bar in with ten, twelve games, and the bartender don’t want it. The bar managers don’t want it. Now you’re the slot guy who is infiltrating into their area.”

Skip echoed the same sentiment while also solidifying that these dynamics can seen as unintended drawbacks of departmentalization:

“One of the old lines that I heard starting in, oh somewhere in the 90s was ‘treat your department like it was your own business.’ That is a dumb thing to tell people because it’s not an isolated department. It’s not just my business that’s kind of on its own island, except the philosophy of treat your department as if it’s your business is causing the problem. And sometimes you will see, if not intentional, but you’ll see conflicts between department where they’re going to counter market against each other for the same business. They don’t take a more holistic approach to this whole thing.”

The survivalistic term was added to reflect the motivation for being overprotective. Overprotectionism in isolation reflected the behavior but did not reflect why the behavior arose. It
was the fear of losing one’s job/department or jeopardizing one’s legacy that gave rise to the survivalism concept.

The complete theory predicts that unintended deviation leading to ineffective analytics is rooted in survivalistic overprotectionism. It is this behavior—easily mistaken as a management quality (protectionism)—that makes data-driven change so challenging and harmful to optimal analytic resource utilization.

Survivalism was identified earlier as a possibility for selective coding, but was set aside as singular overarching code because it was too anthropological in nature. To solidify this point, both ‘survival’ and ‘survivalism’ was input as a search term in academic databases and there was more evidence to suggest that the term was more appropriate in the natural sciences context than that of organizational and managerial sciences. However, when the term was coupled with overprotectionism, the finalized selective code was considered more relevant to the organizational concept of competition and the unintended fragmentation that results from it.

It can be challenged that survivalistic overprotectionism may still be considered a purely behavioral concept. To this point, the main reason why this was finalized as the selective code was because it represented a distinction that was relevant to both the literature and interview data while also not itself, explicitly established in either.

**Course Correction, Analytic Facilitation (AF), and Analytical Bonds (AB)**

In response to the main questions, the MUD provided a theoretical explanation to the reason for why data-driven change was difficult. In doing so, the concept of deviation also brought with it the notion that course correction was the required path back towards ideal data-driven change. In other words, if deviation implied that something was going off-course, then getting to the intended destination is a matter of getting back on course.

How course correction takes shape was not the central purpose of the study because the deviation phenomenon was not known at the onset of the study. The original research questions revolved around explaining the difficulty of data-driven change in hospitality gaming so as to better inform the problem; not actually find the fix. Still, the second research question of applying
theory to inform the problem was important for exploring dynamics may be involved in course correction.

The concept of AF in creating AB may be important to course correction. Introduced at the conclusion of Chapter 2, AB described a specific kind of sender-receiver dynamic whereby the sender of analytic information is providing specialized knowledge to someone that holds decision making power. Furthermore, the MUD suggests that deviation spurred by survivalistic overprotectionism inhibits the formation of AB. With stakeholders so easily inclined to latching on to biases, this can put a strain on analytic resources and prevents high-AF individuals from engaging in developing ABs with other network actors.

One of the interview questions directly addressed this concept by asking the subject if data was more effectively used in some interactions than others. The results were unanimous. All respondents indicated that data was used both more effectively in certain situations than in others.

The following quote by David summarized this concept:

“You’ve got the sender, and you’ve got the receiver, and if both aren’t working to make the junction, you’re going to have a breakdown, so you have to consider the message, and you have to translate it given whoever you’re talking to, whether they’re inclined for data or not. If they’re not, then you’ve got to change your message.”

Beyond what the interviewees said, the first purpose of the quantitative stream was to see if AF could be considered distinct from other related concepts established in literature. This was achieved through a factor analysis of the survey. The second purpose was to see if the AF construct can be predicted through usage statistics. The implication here was to see if usage statistics were a proxy for not only validating AF as a standalone concept, but also, to see if adoption of technology solutions (as measured through usage) can be linked to critical thinking.

What emerged as a possibility through the mixed methods research process was that the embedded instrument could not just serve as a means of validating a construct, but also as a
means for addressing course correction. To this point, while the MUD was developed and survivalistic overprotectionism was identified as the impetus for deviation, it could still be challenged that the framework lacks measurability. Statisticians would have a fair argument in saying that the MUD may provide tighter conceptualizations around the difficulty of data driven change, but it remained that the degree to which things are difficult was still important to understand. In one sense, the concept of overprotectionism did imply that there can be too much protectionism, but as a behavioral term, it remained difficult to distinguish from what might be considered the right amount of protectionism. Applying measurement would also address potential criticism from managers that MUD, AB, and AF provided theoretical explanation, but showed little in the way of being applied in a more practical setting.

**Embedded Quantitative Instrument**

There were two forms of quantitative data collected, survey data and usage statistics. A survey was conducted on employees of a Nevada-based gaming corporation. The survey consisted of 20-Likert scale items and the usage statistics related to a reporting solution inside the same corporation. Those selected for the survey were based on their known usage of the reporting solution.

**Pilot study for instrument development.** The survey was conducted on 47 employees, and corresponding usage data was provided by the company. The data was collected across three properties. The employees worked in various roles, primarily in the marketing department. Positions included hosts, player’s club representatives, supervisors and managers, as well as marketing coordinators, and marketing analysts.

**Sample heterogeneity.** Upon closer inspection of the usage data, there were heterogeneity issues in the data. This was anticipated as a possibility because of the known diversity in employee types. It was apparent in the data that the various roles utilized different reporting solutions so analyzing total report usage would not be representative to the entire sample, as different employees use different reports.

Another issue was that different reports were used across the various properties. Some
properties preferred certain reports over other, which may not have been widely used at other properties. Upon closer analysis, certain employees and reports were isolated to minimize data heterogeneity.

The final dataset was reduced to n=25 and consisted of one employee type: casino hosts. Their usage data was taken for reports that were commonly used across the entire sample. Even prior to analysis, this issue with data heterogeneity indicated that there were inherent limitations in looking at usage statistics without factoring in employee and report type.

With a reduced sample, some delimitations had to be set based on established practices from the literature. Hair, Black, Babin, Anderson, and Tatham (2006) suggested a minimum sample of 50 observations for factor analysis. With a sample of only half the recommended size (n=25) and known heterogeneity issues in the data, the decision was made to treat the quantitative procedure as a pilot study. The original ambition was for the quantitative stream of the broader mixed methods design to serve as a testing of an instrument.

By shifting to a pilot study, the objective of this component of the analysis was instrument development. Johanson and Brooks (2010) recommended sample sizes between 25-40 for instrument development purposes in pilot studies. With all of these considerations taken together, the findings and results from this study were considered limited in their generalizability.

**Factor analysis.** The factor analysis was performed in two stages. For exploratory purposes, an initial factor analysis was performed using the entirety of the survey data (n=47). The subsequent factor analysis was more focused on the research question. This initial look factored in all the question items and was performed to provide a preliminary evaluation of any noteworthy patterns in the interview data.

The interview protocol was framed to elicit feedback from the employee about their relationship with reporting solutions in a general sense. In other words, the respondents were encouraged to think of the survey as a means of providing feedback on reporting solutions and how to improve them. This was explained to the respondent in addition to providing informed consent that described the purpose of the study, which was helping to explain the process of
data-driven change. The survey questions appeared to the respondent as 20 continuous questions without any visible cues that the questions were sectioned as they appear in Appendix A.

Most of the questions on the in-person survey were derived from literature on technology self-efficacy, information access/quality, task-technology fit, and knowledge sharing. This was performed to create a generalized conversation on using reports in their day-to-day jobs. Only four of the questions were directly relevant to the hypothesized construct of AF. Of these four questions, only one was derived from literature (Appendix A). These questions related to AF, grounded in the reflective memos, were examined in exploratory factor analysis to see if AF can be distinguished from other established factors. A factor procedure was run in SPSS 25 applying an oblique rotation. Due to the exploratory nature of this study, an oblique rotation was applied as this method allows for correlation. It was not assumed that the factors are uncorrelated, and the AF factor in particular was introduced and informed by reflective memos.

In the initial exploratory analysis, the Kaiser-Meyer-Olkin (KMO) Test for Sampling Adequacy was .386. The resulting model produced 7 factors based on eigenvalues of >1. The seven factors explained 72% of the overall variance among all twenty question items. Upon evaluation of the factor matrix, cross-loadings on the fifth through seventh factors retained into the model contained several cross-loadings.

The first four factors are described in Table 1: fluency in usage, involvement, communication and sharing, and data access. The second largest factor, involvement contained two questions that were used to explore the theoretical construct of AF. This construct was explored with more focus in the second analysis.

**Reduced sample factor analysis.** With a smaller sample size of only casino hosts (n=25), the exploratory factor analysis was rerun with selected questions. Since the majority of the survey was designed to give the appearance of general engagement with reporting solutions, only the AF and knowledge sharing questions were retained for the reduced sample factor analysis. The other question sections were drawn from literature to provide a more general set of questions for the employee survey. Questions on self-efficacy, information access and quality, and task-technology...
Table 1

**Exploratory factor analysis of overall survey (n=47)**

<table>
<thead>
<tr>
<th>Factor/Survey Question</th>
<th>Factor Loading</th>
<th>Eigenvalue</th>
<th>Variance (%)</th>
<th>Cronbach’s α</th>
<th>M</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fluency in usage</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Comfortable using reports</td>
<td>0.822</td>
<td>3.864</td>
<td>19.320</td>
<td>0.751</td>
<td>4.174</td>
</tr>
<tr>
<td>Regularly use reports</td>
<td>0.584</td>
<td></td>
<td></td>
<td></td>
<td>4.295</td>
</tr>
<tr>
<td>Strong ability to use reports</td>
<td>0.759</td>
<td></td>
<td></td>
<td></td>
<td>4.477</td>
</tr>
<tr>
<td>Flexible and interactive</td>
<td>0.628</td>
<td></td>
<td></td>
<td></td>
<td>4.227</td>
</tr>
<tr>
<td><strong>Involvement</strong></td>
<td></td>
<td>2.733</td>
<td>13.665</td>
<td>0.773</td>
<td>4.174</td>
</tr>
<tr>
<td>Involvement in change</td>
<td>0.704</td>
<td></td>
<td></td>
<td></td>
<td>3.614</td>
</tr>
<tr>
<td>More training</td>
<td>0.859</td>
<td></td>
<td></td>
<td></td>
<td>4.024</td>
</tr>
<tr>
<td><strong>Communication and sharing</strong></td>
<td></td>
<td>2.353</td>
<td>11.765</td>
<td>0.685</td>
<td>4.174</td>
</tr>
<tr>
<td>Share reports with team</td>
<td>0.762</td>
<td></td>
<td></td>
<td></td>
<td>4.250</td>
</tr>
<tr>
<td>Communicate with reports</td>
<td>0.827</td>
<td></td>
<td></td>
<td></td>
<td>3.878</td>
</tr>
<tr>
<td>New learnings shared</td>
<td>0.568</td>
<td></td>
<td></td>
<td></td>
<td>4.372</td>
</tr>
<tr>
<td>Data can be contradictory</td>
<td>0.601</td>
<td></td>
<td></td>
<td></td>
<td>2.907</td>
</tr>
<tr>
<td><strong>Data access</strong></td>
<td></td>
<td>1.758</td>
<td>8.791</td>
<td>0.549</td>
<td>4.174</td>
</tr>
<tr>
<td>Right amount of data</td>
<td>0.869</td>
<td></td>
<td></td>
<td></td>
<td>3.568</td>
</tr>
<tr>
<td>Reports are widely used</td>
<td>0.631</td>
<td></td>
<td></td>
<td></td>
<td>4.318</td>
</tr>
<tr>
<td>Company data availability</td>
<td>0.512</td>
<td></td>
<td></td>
<td></td>
<td>3.818</td>
</tr>
</tbody>
</table>

*Note:* Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy = 0.386. Bartlett’s Test of Sphericity = 327.460 (190 df, p<.0001).

fit were not included in the reduced sample factor analysis. These constructs were important to the methodology, but were not central to the research questions.

Knowledge sharing was retained for the reduced sample factor analysis. Knowledge sharing takes on a variety of definitions (Tohidinia & Mosakhani, 2010), but is summarized by Bartol and Srivastava (2002) as taking place when members share organization-related information, ideas, suggestions and expertise with each other. Both Ellinger and Cseh (2007) and Woiceshyn and Falkenberg (2008) discuss the concept of facilitation as critical to workplace learning, problem solving, and the creation of new organizational knowledge.
Despite the similarity to AF, the knowledge sharing questions were worded differently. The knowledge sharing questions, derived from Tohidinia and Mosakhani (2010) asked if the respondent agreed with the concept of sharing and if they participated in sharing knowledge as they related to the reports. The AF questions, went deeper in asking respondents to what degree they may want to get involved in the report building and changing process. This distinction between knowledge sharing and involvement takes a cue from Constant, Kiesler, and Sproull (1994), which found that motivation to share technical expertise varied by individual depending on prosocial attitudes, organizational norms, and the kind of information involved. To compare this to the current study, the notion that employees believe in the spreading of data-driven change may be distinct from the desire to actually be involved in it.

There were five knowledge sharing questions and four AF questions totaling to nine questions. To focus even more on the individual’s behavior as it related to sharing and facilitation, three questions were removed from the factor analysis, two from the knowledge sharing section, and one from the AF section. The removed questions did not ask directly about the individual’s behavior and instead were directed more towards their perceptions on their workgroup and the organization. The remaining six questions contained either the term me or I. The removed questions did not contain these terms oriented towards the individual respondent.

The data was screened for width-based outliers. In this inspection, one observation was removed from the data because the individual had no reported data usage, which was anomalous. Furthermore, the location of the outlier did not significantly impact the resultant coefficients of the subsequent model.

With the remaining 24 data points, the Kaiser-Meyer-Olkin (KMO) Test for Sampling Adequacy was .688, which is considered fair (Hair et al., 2006). The procedure resulted in two factors that loaded along the lines of the known differences in the knowledge sharing and AF constructs (Table ??).

By evaluating the factor matrix, the first factor related to knowledge sharing suggested a personal disposition to the sharing of knowledge. The second factor related to AF suggested
personal change involvement in playing an active role in learning and changing reports. The absence of cross-loadings suggested that getting actively involved in data-driven change stood apart from the more passive concept of believing that knowledge sharing was important. The two factors with Eigenvalues explained 69% of the overall variance.

Table 2

*Exploratory factor analysis of AF and knowledge sharing (n=24)*

<table>
<thead>
<tr>
<th>Factor/Survey Question</th>
<th>Factor Loading</th>
<th>Eigenvalue</th>
<th>Variance (%)</th>
<th>Cronbach’s α</th>
<th>M</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge sharing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>To me sharing knowledge with others is beneficial.</td>
<td>0.78</td>
<td>2.652</td>
<td>44.207</td>
<td>0.766</td>
<td>4.403</td>
</tr>
<tr>
<td>I share things I see on reports with team members.</td>
<td>0.84</td>
<td></td>
<td></td>
<td></td>
<td>4.250</td>
</tr>
<tr>
<td>When I learn something new about reports, I tell my colleagues about it.</td>
<td>0.85</td>
<td></td>
<td></td>
<td></td>
<td>4.250</td>
</tr>
<tr>
<td>Analytic facilitation</td>
<td></td>
<td>1.479</td>
<td>24.642</td>
<td>0.734</td>
<td>4.056</td>
</tr>
<tr>
<td>I would combine certain data across different reports.</td>
<td>0.81</td>
<td></td>
<td></td>
<td></td>
<td>4.125</td>
</tr>
<tr>
<td>I would want to get involved in changing the report content.</td>
<td>0.88</td>
<td></td>
<td></td>
<td></td>
<td>3.792</td>
</tr>
<tr>
<td>I wish there were more training on certain reports.</td>
<td>0.71</td>
<td></td>
<td></td>
<td></td>
<td>4.250</td>
</tr>
</tbody>
</table>

*Note:* Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy = 0.681. Bartlett’s Test of Sphericity = 37.934 (15 df, p=.001).

Mean scores were calculated for the personal change involvement factor by averaging the scores of those items from the original data. These scores were then used for the subsequent regression analysis. The objective was to see if usage data could predict the AF construct.

**Regression analysis.** The usage statistics were then matched with the survey data to predict the personal change involvement factor scores for each individual. Upon inspection of the normality of the usage statistics, a right skew was observed indicating that some users ran reports...
at a magnitude far greater than the mean. Therefore, a natural log transformation was applied to the usage statistics.

A simple linear regression was performed to see if usage can be a means of predicting AF. The model was significant at a p-value of .0001. The regression explained 38% of the overall variance. The beta coefficient interpretation showed that for every unit increase in the AF factor, there was a .615 log unit increase in reports run (Table ??). Usage can predict the desire to get involved in data-driven change.

Table 3

Regression summary for predicting AF

<table>
<thead>
<tr>
<th>Variable</th>
<th>B</th>
<th>SE(B)</th>
<th>β</th>
<th>t</th>
<th>Sig.(p)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural log of total reports executed</td>
<td>0.430</td>
<td>0.118</td>
<td>0.615</td>
<td>3.656</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Note: R² = 0.378

Merged Results

The main research question was understanding why data-driven change is difficult in hospitality gaming. In addressing this question the analysis first parsed out the challenges of data-driven change to explain the differences between what was intended and what actually happens. This deviation implied that there was a theoretical distance in which the intended and the actual outcomes deviated from each other. While not entirely measurable, at least not after the qualitative analysis and before the quantitative analysis, the theory at least implicated the idea that the further the distance, the more difficult achieving the desired change became. Taken at its face, this also implied that to attain intended change, the distance between the intended ideal and the unintended actual must be kept to a minimum, either through prevention or course correction.

The emergent conceptual model identified the impetus for why data-driven change is so hard: survivalistic overprotectionism resulting from the unintended consequences that arise from analytic resource decisions. The MUD expands the discussion on culture, resistance, and the silo effect. The MUD unifies these known concepts into a theory grounded in data from the
hospitality gaming industry. The primary qualitative stream of research shows that overprotectionism lies at the heart of many of the challenges associated with data-driven change. Secondarily, despite shortcomings in sample size, a significant result of predicting the AF factor with usage scores was produced. Within the confines of a delimited pilot study, the regression model does indicate that a significant relationship can be found between AF and usage statistics. The conclusion from the discussion and the regression shows that the number of times reports were run is generally directional to AF score, but further refinement of usage statistics is necessary to further help validate and predict AF.

The broad conclusion was drawn that little to few runs will tend to correlate with low AF and conversely, high usage will correlate with higher AF. However, this did not rule out the possibility that certain employees run reports just a few times and be able to disseminate as much as someone who runs a report many times over and disseminates very little. This was not necessarily a limitation and was in fact considered illuminating to the concept of effective usage. The concept of effective usage was considered key in what it meant to be analytically facilitative. It was concluded that AF might be measurable through raw usage scores. By this same token it was also determined that raw usage statistics should not be considered an accurate predictor of AF—they are at best a coarse statistic. It only revealed how many times something has been executed and said very little of how the reports were used. It did not show how infrequent usage could still be effective when done in combination with the gathering of other forms of business intelligence.

The pilot study was successful in identifying that usage could be used as a rough proxy for measuring data-driven adoption. Improving predictive accuracy for a similar study would require stricter controls with respect to heterogeneity issues around report type and employee type as different employees are likely to use reporting solutions in different ways. Furthermore, raw execution count data was not determined a complete indicator of how reports were effectively used. Ultimately, the pilot instrument did show promise but will require further refinement and scaling up to improve its ability to predict.
The broad conclusion of the merged results was that deviation occurs unintentionally. Furthermore, this unintentionality made the identification of the warning signs hard to spot. The qualitative stream was the priority research stream in the embedded design.

The primary theoretical contribution of this research is the MUD, which helps explain the difficulty of data-driven change. The MUD helps the data-driven change process by identifying pitfalls of otherwise well-intended strategic decisions.

Firstly, the MUD provides the potential for early detection of underestimating the social and technological complexity of achieving data-driven ideals. Secondly, the MUD provides a framework for preventing unnecessary competition and silo effects that can arise from organizational structure decisions. Thirdly, the MUD identifies that overprotectionism can result in an inefficient usage of analytic resources, driven not by hypothesis testing and scientific method, but instead to produce favorably biased performance narratives. This may easily be mistaken as data-driven change, when in fact it remains a facade of protectionism and competitiveness. In reality there may be overprotectionism, driven by over-reporting and confusion over the analytic role in organizations.

The embedded quantitative instrument also exposed the possibility that AF, while still a preliminary construct, can also be something that goes unnoticed by managers. This is because of its distinguishing characteristics from a more general belief in knowledge sharing. The commonality of both the quantitative and qualitative streams of research is that data-driven change may appear to managers as being more ideal than reality and that there are behavioral and network dynamics to consider in interpreting what is observed on the surface.
CHAPTER 5

Discussion

The Model of Unintended Deviation (MUD) represents a new model for explaining the difficulty of data-driven change in hospitality gaming. It is informed through the qualitative research method of grounded theory, which is the priority research stream of the broader design. The theory is helpful to data-driven change because it recognizes where otherwise well-intended strategic decisions produce results that deviate from an intended vision. The MUD explains from multiple perspectives, the impetus for this deviation. The model recognizes that the silo effect (Tett, 2015), can cause network actors to misuse data resources. Managers may be misled into believing that data-driven change is occurring. To this point, overprotective behaviors may not be receiving a sufficient degree of critical attention.

The embedded quantitative instrument produced some suggestive evidence that analytic facilitation, a set of behaviors and activities unique to data-driven change can be predicted through usage statistics. While the raw usage score did not show how the employees used reports, the results raise the issue of how to better define effective usage so as to manage it against a predetermined standard.

The objective of this final chapter is to go into further details about what the data and findings show and what they mean to both academe and to industry. This begins with a discussion on the implications of the findings with respect to theory followed by a discussion on what the theory means to practitioners. The managerial implications are divided into two subsections, one addressing hospitality gaming specifically, and the other addressing the broader areas of network and organizational sciences.

Theoretical Implications

The idea that change is a matter of unintended deviation and course correction challenged the prevailing wisdom established by McAfee and Brynjolfsson (2012) and Bean (2017, April), that the difficulty of data-driven change was a matter of overcoming resistance. One difference
between resistance and deviation was found to be that resistance can imply an oppositional force. This falls in line with criticism of change research made by Dent and Goldberg (1999). It was argued that by focusing on opposition, resistance overlooks the possibility that change does not necessarily have to overcome anything. The deviation model proposed in the current research suggested that achieving intended change is a process of recognizing (and even preventing) drift and correcting course accordingly.

While change being difficult is implied in both deviation and resistance perspectives, the deviation model suggests that the concept of data-driven decisions are bought into by all key stakeholders. The resistance concept can imply that stakeholders were resistant to begin with. By addressing change difficulty as deviation and course correction rather than an oppositional force to resistance, this plays out differently in the MUD; the visual representation of data-driven change (Figure 4). The latter implies a linear back-and-forth concept whereas the former works across multiple vectors, which enables the view of an optimum path, a deviating path, and a path for course correction.

Another prevailing interpretation on the difficulty of data-driven change was cited as cultural issues. Organizational culture has been referred to as a system of shared meaning held by individuals that distinguishes an organization from others (Robbins & Judge, 2013). Although a pilot study, the embedded quantitative research showed the potential for AF as playing a key role in creating ABs.

This rested on the notion that data-driven change was distinctly difficult from other forms of culture change. As opposed to simple top-down directives, data-driven decisions required high-level decisions being entrusted to those in analytical roles that have specialized knowledge but lack formal decision making power. This concept was broached in previous literature as the HiPPO problem (McAfee & Brynjolfsson, 2012), which noted that data-driven decisions no longer fell to the Highest Paid Person’s Opinion.

MUD, AF, and AB extended this discussion and addressed the shortcomings of the culture argument. This was achieved by concluding that attaining shared meaning in a data-driven
paradigm is uniquely challenging, especially given that stakeholders find more incentive in applying biases to analytics than in accepting objective conclusions. This was shown to be a direct reflection of their protective and survivalistic instincts. This may also go unrecognized as protectionism was considered a necessary and valid quality of managers, but overprotectionism was determined to produce adverse effects.

The notion that survivalistic overprotectionism resulted from unnecessary competition resulting from departmentalization corresponded with the silo effect discussed by Tett (2015). The understanding that actors will behave in strange ways was strengthened with the current study.

Both the MUD and the silo effect identified that the structure of the organization can play an impeding role in driving desired change. Both perspectives also highlighted that the decisions to structure organizations in a certain way was not purposefully done to create future problems. Tett (2015) applied an anthropological lens to the difficulty of change. The MUD drew very similar conclusions as Tett (2015), but a distinction was drawn in that the MUD approached the problem with a social network lens. Field studies and anthropological observations are important to diagnosing data-driven change difficulties. Applying a social network analysis provided not only an additional theoretical lens but also, given its built-in metric components, an opportunity for scale development.

MUD also predicts that in a deviating path away from the intended path, undesirable effects arise. If a firm seeks competitive advantage through social and intellectual capital as proposed by Nahapiet and Ghoshal (1998), then survivalistic overprotectionism gone unchecked, would give rise to the presence of biases. These biases could normalize and lead to greater deviation and likewise, require more course correction. While change can be thought of as a communication based process occurring at the individual interaction level (Ford & Ford, 1995), change can also be thought of as a collective whole of many interactions.

Nahapiet and Ghoshal (1998) discussed relationships between social and intellectual capital as a source of organizational advantage. The authors suggest that through the processes of social exchange and the combining of activities, intellectual capital is formed. By doing so effectively,
firms can gain a competitive advantage. It is not just the activation of the skills in the workforce, but also, the structure of the network that maximizes the opportunities for combination and exchange to occur.

This linkage between interaction level and organizational dynamics—from micro to macro—drawn from Nahapiet and Ghoshal (1998) is comparable to how the MUD, AB, and AF explain the difficulty of data-driven change. The MUD addresses data-driven change at the organization level while AB and AF addresses it at the interaction level.

Ultimately, the MUD provides a cleaner and more holistic conceptualization of the difficulty of change—compared to that of resistance and cultural issues. Furthermore, AF and its role in creating strong ABs provides a means to understand how deviation from intended change can be corrected for or prevented. This differs from existing prescriptions on addressing change difficulty which have fallen short in providing valid theoretical frameworks. The key difference is that AF posits that the desire for managers to get involved in data-driven change is distinct from the simple belief in its promise. Previous research did not go far enough to look for this distinction. In this sense, some managers could be falsely identified as being truly invested data-driven change.

In relation to the current literature, the MUD is not completely unprecedented in its approach to challenging existing paradigms of change. Unintended change was discussed in Felin and Foss (2009) for example that questioned the concept of organizational routines and suggested that unintentional changes may occur at the microlevel, which can grow to institutionalize at the macro-level. Researchers emphasized that more attention should be given to developing micro-foundations around work routines. This can be performed through the examining micro-elements of organizations that include a better understanding interactions between individuals.

Another example can be found in March (1981), which discussed the idea that change would naturally create “unanticipated consequences to ordinary actions”. It is suggested that if an organization is changing faster than it can adapt to those changes, then processes can more easily
be deemed as ineffective. Confusion and unintended outcomes are therefore natural for an organization adapting to change.

Similar to deviation, Quattrone and Hopper (2001) proposed a model for organizational drift to replace existing paradigms of change. It was argued that actors involved in change are not always completely aware of their orientation in the change process despite recognizing an intended direction. Decisions on how to organize will not always be optimal and move along a perfectly linear path. Unpredictability through the change process and going through a multitude of positions and states are factored into this drift model of change.

These examples demonstrate that change can be illustrated in a similar fashion to unintended deviation and provide additional grounding to the current study. Differing from these examples, the MUD is focused specifically on data-driven change, and not just change in general. It achieves this by addressing AF and AB as well as the role that biases plays in the achieving change. Furthermore, MUD addresses how the combination of survivalistic overprotectionism amid limited resources leads to the misuse and confusion around the analytic function within organizations.

Finally, the setting and sample of this study should be considered in relation to the development of theory specific to the field of hospitality. To this point, Ogbonna and Harris (2002) summarized a discourse among scholars as to the unique aspects of the hospitality industry with respect to human resource and culture management. Hospitality is sometimes seen as a field with a greater population of low-skilled workers (Ogbonna & Harris, 2002). Also, this conclusion has led researchers to believe that hospitality may not be as conducive to the effects of human resource management practices as other industries (Price, 1994). While these points are part of an ongoing debate, the suggestion that the hospitality industry has a different baseline skill level than other industries highlights the argument that theory development on data-drive should take into account be industry specific dynamics.
Managerial Implications

Proponents of data-driven change are right to argue that leadership, culture, human resources and technology are all key to widespread adoption of Big Data (McAfee & Brynjolfsson, 2012). However, the findings from this study prove that they oversimplify the problem when they claim that cultural challenges including resistance are all that needs to be overcome (Bean, 2017, April). The implications of the current study laid out an argument that not only are these claims exaggerated, but they are also misunderstood.

The MUD predicts that idealized change where effective analytics are being performed all the time may never be achieved, and that inefficient utilization of resources and bias formation are unavoidable. In this conceptualization, resistance and the desire to change the culture are not the wrong diagnoses. Rather, they are symptoms of a deeper problem that is overprotectionism. Addressing this particular behavior is a more targeted description of the root of the difficulty of change.

Individuals in an opportune position to performing targeted remedies would be the strategic change agent. Change agents can be managers or non-managers, current employees of the organization, or newly hired employees, or outside consultants (Robbins & Judge, 2013). It is this person’s role to “develop a climate for planned change by overcoming resistances and rallying forces for positive growth” (Westover, 2010). The implication here is that the change agent could observe the nuanced phenomena that existing change management frameworks are not quite capturing.

Instead of overcoming resistance as suggested by Westover (2010), which implied changing people, the change agent could instead consider the MUD and focus away from people problems to that of analytic resource utilization. If bias-motivated analytics are occurring more frequently than objective data-driven analytics, then the change agent does not necessarily have to implicate the bias-driven requestor and consider the contextual factors that lead to overprotectionism.

The change agent could assess the situation such that the motivations of the person are questioned, rather than the person itself. This may lead to a more sympathetic response measure
that acknowledges that protectionism is a sound motivation for requesting analytics, but overprotectionism can lead to the misuse of limited analytic resources, which is not beneficial to the whole of the organization. Tett (2015) is an important contribution in understanding how organizational silos lie at the root of protectionistic behaviors.

Tribalism was a common thread to both the MUD and the work of Tett (2015). Tribalism was considered within the coding process but was determined to be more akin to anthropology terminology, which was precisely the approach employed by Tett (2015). The overprotectionism construct was adopted for selective coding instead. It was considered distinctive to tribalism in that it suggests that there is an excessive component of an otherwise ideal behavior.

Tett (2015) accurately identified the linkages between organizational silos, the unnecessary competition and irrational behaviors that come with it. There are direct parallels between the silo effect and the MUD. However, the MUD addressed the unique difficulty of data-driven change such that senior leaders may otherwise be misled into thinking that data-driven change is occurring, when in fact, the problem is worsening.

The data showed that salesmanship and tactful communication are just a couple of the soft skills that are considered to be desirable for effective analytic presentation in today’s gaming companies. Coupled with management levels being protective, this can create a facade that data-driven change is occurring because the numbers are there to back up the narrative. However in reality, department leaders may be overprotective and latching on to biases and digging in for the sake of their own survival. From the data, this has been shown to be an inefficient usage of analytic resources.

For change agents, understanding the nuances around a false facade of data-driven change is important depending on the brokerage role of the change agent. The precise brokerage role of the change agent in relation to different projects may vary, even inside the context of an individual interaction. Brokerage occurs when one actor serves as a bridge between two other actors, whom themselves lack a direct connection to one other (Spiro, Acton, & Butts, 2013).

With respect to the MUD, in a data-driven organization, influence may not always default to
the HiPPO (highest-paid person’s opinion). Brokerage roles may play an important function in understanding deviation. Equipped with the understanding that resistance may be merely the manifestation of overprotectionism, the broker may approach a change situation differently. Instead of appeasing to network actors by developing reporting and analytics that is requested, the broker may instead address the motivations, biases, and resource limitations first, before falling into developing ineffective analytics such as over-reporting—an unintended drawback of deviation.

By drawing attention to organizational and interactional dynamics, the MUD, AF, and AB also advanced the discussion on data-driven change by going further than to simply explain the importance of top-management buy-in. Just below this top layer of management, interactions related to analytic resource allocation and departmentalization are key forums for change agents to take note.

Ford and Ford (1995) discussed the role of meetings and conversations in change efforts. Specifically, they recognized that intentional change has classically been thought of as a process of top management commitment or as a balance of forces for and against the change. Ford and Ford introduced the framework of change as a “communication-based and communication-driven phenomenon.” More specifically, the conversations that managers use to create, sustain, focus, and complete a change contain and take shape in forms that could be coded for in data.

By combining Ford and Ford (1995) with the knowledge that stakeholders may employ a facade of informed analytics to support their own self-interests, change agents may be better equipped to manage interactions towards the intended path of objective data-driven decisions, as opposed to a path that leads the organization astray from their data-driven goals.

This point spoke to the theme found in the data that effective analytics did not imply that the analytics were performed properly. Change agents should question whether a report request from a manager may be in one sense warranted and intentional, but in another, the motivation of the request may be based in biases rooted in survivalistic overprotectionism.
Hospitality Gaming

With respect to hospitality gaming, the findings show that the inherent diversity of hospitality gaming may heighten organizational sensitivity to unintended deviation—more so than industries that are more uniform and have fewer revenue streams. This results from the notion that the more departments there are, the more subcultures and subnetworks can form. Larger firms will also contain multiple resort assets across various markets. Divisions created through departmentalization and organizational structuring may create unintended and unhealthy competition between groups, giving rise to survivalistic overprotectionism. The more subgroups that there are, the more analytics have to be communicated across a diverse range of stakeholders; in this sense, AB may be harder to develop. Leaders of these groups and particularly those that are struggling to keep their numbers strong can become concerned over their own survival as a business unit. This in turn leads them to becoming protective, and worse yet overprotective. In this heightened sensitivity, it makes latching on to biases all the more justifiable, even if it means diverting from the ideal path of making informed, objective, data-driven decisions.

Today’s integrated resorts are a prime example of why data-driven change in the hospitality industry should be considered unique comparatively to other industries. The hallmark characteristic of integrated resorts is the emphasis on non-gaming amenities (MacDonald & Eadington, 2008). Over the years, the diversification has only increased with more and more entertainment options for visitors. The emergence of the of the integrated resort has happened in parallel with the rise of Big Data analytics. This poses a unique situation. Managers of integrated resort properties face a conundrum because non-gaming amenities are the strategic differentiators from a marketing perspective but drive little to the bottom line. Comparatively speaking, gaming has is less differentiation across a competitive set of integrated resorts, but bring a significant portion to the bottom line (Lucas & Kilby, 2012). Today’s player clubs look to capitalize on building loyalty programs that tap into the various purchasing patterns that can now happen in an integrated resort. This is all reliant on information technology. The desire for more interconnectivity within a business model where departmental income is disproportionate to the
customer experience brings the need for data-driven change management into focus. In this setting, the MUD can be applied prior to making important resource decisions that entail the connection of data systems. Understanding the potential pitfalls and natural challenges that arise—or unintended deviation—are key to preventing not just technological headaches, but political ones as well.

When deviation has already occurred, it is important to be cognizant of managers latching on to biased narratives. The underlying survivalistic overprotectionism leads to it can be discussed in the realm of loss aversion, advanced by Tversky and Kahneman (1991). It predicted that losses and disadvantages have more sway cognitively speaking, than gains and advantages. Pope and Schweitzer (2011) demonstrated that even in high-stakes competitive environments, the cognitive bias of loss aversion persists. This potentially related concept is drawn from behavioral economics. While a direct connection has yet to be drawn empirically between survivalistic overprotectionism and loss aversion, the implication remains that individual actors are not immune to incorporating biases into their thinking despite perceived changes to competitive forces and a corresponding will to survive.

Being oblivious to biases is important to note for hospitality managers, especially since deviation can easily go unnoticed; the deviation is of course unintended. The unrecognizability of deviation may persist for longer periods compared to other business types that do not have as much diversification. Knowledge transfer has also been found to be uniquely challenging in hospitality because of the demands of a service-heavy business model. The constant flow of day-to-day demands makes transferring knowledge more challenging in hospitality; knowledge transfer is preferred as spontaneous face-to-face interactions rather than through structured social interaction such as workshops (Yang, 2009). It is then important for senior leaders to understand the inherent limitations of knowledge transfer in the hospitality industry in concert with their desire for data-driven change, especially given the complexity of the technology. An overgeneralized view of this aspect is potentially very costly.

Firms still operate under the guise advanced by hospitality researchers that technology, data
solutions, and knowledge management are strategic problem solvers (Gronau, 2002; Okumus, 2013). However, as the current study has shown, adding more layers of management around specialized and highly technical knowledge may only exacerbate the difficulty of data-driven change. Simply believing and investing in Big Data’s promise are not by themselves the solution to data-driven change. Hospitality managers would be keen to define effective usage prior to making key investments and structural decisions around analytics as well as monitor against predefined expectations after the rollout of data-driven change initiatives.

**Network and Organizational**

AF and AB in particular may also be applicable to better understanding change—and the inhibitors of it—from a social network perspective. To review, Gladwell (2006) is a popular reference point for change as a social contagion phenomenon. Its summarization does align with the academic research in that diffusion generally follows a normal distribution with the early adopters and the laggards representing the smallest populations. Diffusion can also be viewed as a left-to-right time path along this normal distribution. These concepts are key to understanding that information and resources flow through different networks in different ways (Scott & Carrington, 2011).

To this point, there may be information bottlenecks in organizations that are vital to the spread of information (De Nooy, Mrvar, & Batagelj, 2011), and computer models have shown that diffusion occurs more slowly in networks with a few highly connected nodes than random networks (Gibson, 2005). Social network analysts may find value in the AB as an assignable value to relational ties—the stronger the bond, the higher the value of the tie. This could be expressed in a number of ways including line thickness and length to name a few.

The AF construct may be useful to assign a value to the nodes in a social network graph—the higher the AF, the higher the value assigned to the node. Assigning values to AF and AB in a network context could inform the speed at which data-driven change diffuses across a network so as to better inform decisions to rollout change in a more strategic manner. It remains
that collecting informal social network data is sensitive and challenging. This does not discount the fact that managers still rely heavily on organizational charts (Rummler & Brache, 2012), which do not express AF and AB. By incorporating both perspectives, understanding how stakeholders communicate on an analytical level can help to improve restructuring decisions and in the formation of teams.

Traditional organizational charts may be effective at diagramming bureaucratic separation (Molina, 2001), but is poor at showing cross-functional workflow (Rummler & Brache, 2012). Understanding data-driven change at the interaction level is fundamental to the constructs of AF and AB. Because these concepts deal with decision making power, in a way, it challenges organizations to rethink the centrality of decision making within the organization.

This becomes important as Zabojnik (2002) noted that there was a trade-off between centralized decision making and delegation such that the latter leads to better utilization of information scattered through the lower levels of the organization but brings with it a loss of control for the upper-level managers. This is not to imply that the traditional organizational chart becomes obsolete. Rather, by combining the organizational chart with MUD, AF, and AB, firms may gain an additional perspective to strategic decisions related the optimal use of analytic resources.

**Limitations**

The first limitation to discuss is inherent to the embedded mixed methods design. While the qualitative stream applied grounded theory to produce new theory, the theory itself remains largely untested. In grounded theory, the empirical data is used to create new theory, not to test an existing one. More validation of the framework is required to strengthen the theoretical claims of MUD. AF provided some initial means of testing, though not of the MUD itself. The quantitative stream was secondary to the qualitative stream.

It was in this quantitative stream where an instrument was tested to distinguish AF, which was a construct devised as a response to the gaps in the literature on data-driven change. Although further grounding through a quantitative instrument produced significant results, it is
important to emphasize that conclusions related to AF remain secondary to the MUD, which was informed by the primary qualitative design. This limited the study’s ability to validate the connectivity of micro and macro level network phenomena. However, discussing the lack of generalizability in this study was also an opportunity to consider the unique aspects of the hospitality gaming that make it an opportune setting for studying change management.

While the quantitative strand included interviewees from a wide range of professionals in hospitality gaming, the quantitative strand only included participants from one specific type of organization. These employees spanned three different properties within a single corporation but nonetheless, findings drawn from this portion of the study are limited in its generalizability. Results will vary in different organizations where employees have different kinds of relationships with analytic solutions. Furthermore, the customer/casino type (locals versus destination resort) may also dictate how analytics get used. It was not determined whether the organization in the current study would consider themselves to be data-driven. Usage statistics may be different in organizations that are self-proclaimed to be data-driven.

The survey sample also only included one employee type: casino hosts. In one sense, this validated the notion that AF is an attribute that not just analysts who have the title participate in interpreting and drawing analytic conclusions. However, hosts represent just a small area of employees in the broader context of data-driven change. The survey instrument was only conducted on hosts, while the qualitative interview was conducted on managers in a variety of areas. While the instrument was deemed significant in that usage can predict AF values within the limits of a pilot study, the instrument must also be repeated across other populations to be considered generalizable.

Although only looking at casino hosts for this study is limiting, these employees also provide a unique lens to the difficulties of data-driven change. The job of the casino host is to build and develop relationships with high-value players. Their role requires of them to build one-to-one relationships to develop long-term loyalty and patronage. They are hired primarily for their soft skills. They spend a significant portion of their time on the casino floor, talking to guests
at their desks, or on the phone keeping contacts with players and inviting them to special events.

While they are not hired for their prowess in Big Data analytics, hosts do rely heavily on reports produced by analysts. Casino marketing then becomes essential as player reinvestment expenses must be managed in relation to the value of the players; this is where analytics come into frame. This interaction—or analytic bond—between a front-facing employee and a back-of-house employee reveals firstly that not just managers are part of the data-driven change process. Secondly, the job functions of the host role show that the day-to-day demands in hospitality make the transferring of analytical concepts a unique situation.

Hosts are constantly looking at player behaviors. These employees are incentivized based on their ability to manage reinvestment expenses. To do so, they rely on reporting solutions to help with their player evaluations. Hosts are both limited in time for analytics but also heavily reliant on analytic tools. Yang (2009) discovered that in hospitality, given the work demands, knowledge transfer is most preferred as a spontaneous face-to-face interaction. The report usage for the hosts can be spontaneous in nature, reflective of the players that walk into their offices. With day-to-day demands, hosts are not incentivized to put a high priority on involving themselves in data-driven change. Still, they play an important role in driving business from the company’s most valuable segment. Companies should be wise to recognize that the very nature of the hospitality industry may contribute to the misrecognition of unintended deviation. Further, the ability to distinguish survivalistic overprotectionism may be more challenging in the hospitality industry given its constant and spontaneous demands.

The research was also focused on data-driven change only within the realm of property management. There are other realms of the hospitality sector that may differ in its relationship with analytics. Firms that are more Internet facing such as online travel agencies and review websites are ingrained into the hospitality gaming sector, and are heavily tech-driven. Slot manufacturers and gaming systems vendors are also an important aspect of the broader sector. Research in these domain may produce different results. These firms are structurally very different from property operations. Their business models are more closely tied to cutting-edge
technological functioning rather than just end-user experiences. Because these organizations have a more involved relationship with advanced technologies, AF and AB may be less of an issue, or it may differ in the way it is described when compared to the responses provided in the current study.

Finally, while a grounded theory was developed (MUD), the embedded quantitative instrument was only able to produce valid results within the confines of a pilot study. The instrument ultimately requires further development. Within this limitation, the quantitative analysis produced significant results that brought some validity to the AF construct but generalizability remained an issue. In a certain way, the limitations shed light on the elusive but important concept of usage, and in particular, effective usage. Taking a simple number of executions was the metric used in this study as a determinant of the AF construct. The usage statistics simply looked at frequency, which did reveal significant correlation to AF but much is left to be discovered as to how users are applying data to make decisions.

**Future Research**

The main research question of this dissertation was to explore what makes data-driven change difficult in hospitality gaming. The answer lied in a disconnect that occurred just below the top management level where strategic resource and departmentalization decisions were made. Despite leaders being bought in, outcomes were less than ideal. Decisions trickled down based on initial buy-in. However, things began to deviate from objective and properly performed data-driven analytics. Instead the unintended path led to undesirable outcomes that can often arise. This deviation was commonplace as the qualitative data revealed.

While the MUD helped to explain the difficulties of data-driven change, it also created more specific research questions designed to shed more light to the subtleties of misdiagnosing data-driven change problems. One question for future research would be to explore the differences between protectionism and overprotectionism. This was identified as a key behavior that can lead organizations astray from their desired data-driven paths—protectionism representing a fair and worthy trait whereas overprotectionism is considered unfavorable.
Understanding these behaviors across different organizational types and structures would also provide important insights in relation to the MUD.

Another question for future research relates to the notion that analytic presentation from sender to receiver can be both effective and improper, and conversely, they can be ineffective and properly executed. Both these questions relate to interaction dynamics whereby soft skills and biases play a role in whether or not a data-driven recommendation is both accepted and appropriate, which represents the ideal situation. Both these questions would fall into a more broader research question of what kinds of behaviors and interactions mislead stakeholders into believing they are helpful when in fact they are not.

With respect to survivalistic overprotectionism, Ridgeway and Berger (1986) discussed the behaviors of legitimation and dominance, which is exhibited by high ranking actors that engage more effectively in directive or domineering behaviors. These behaviors may be observable in the data-driven change context. While Mazur (1985) identified specific dominating behaviors in primates including explicit commands, staring another down, and shouting. Ridgeway and Berger (1986) posited that dominant behaviors should be understood as a process of legitimation, particularly in task groups. This is relevant to research on data-driven change agents, as any strategic decision must be supported by data. However, determining to what degree the data is legitimizing the argument and not other behaviors such as salesmanship or dominance highlights the possibility that these dynamics may be discernible in an observational study on protectionism. Studying these behaviors across multiple organization types would also provide important insights applicable to the MUD.

The MUD also informed future research in knowledge management. To review, knowledge management involves the strategies and processes of identifying, creating, capturing, organizing, transferring, and leveraging knowledge to help individuals and firms complete (O’Dell et al., 1998). The MUD predicts that deviating from the desired path towards data-driven change may not be immediately recognized by the organization. The MUD also predicts that deviation can lead to poor analytic resources utilization and reporting waste. In combination with knowledge
management frameworks, the MUD could be extended to inform how to improve efficiency with respect to the volume, distribution, and prioritization of data, intelligence, and information.

The concept of usage can serve as means to evaluating data-driven adoption. However, the raw number of reports executed fell short of producing generalizable results in the current study of predicting AF. Future studies should continue to examine the concept of effective usage across different employee groups and organizational types. Understanding the way in reports get combined with other intelligence and how they materialize into decisions would be a promising area for investigation.

Getting to the ‘how’ of the usage concept, and not simply the ‘how many times’ as was done in the current study, may provide insights as to value-added usage versus usage in general. Furthermore, the pilot study suggests that AF could stand on its own as a construct distinct from knowledge sharing. Future research should not only continue to explore AF and its role in creating AB not just to establish more validity, but also, to look at the relationship between usage and profitability. The current study produced findings that were primarily relevant to the domain of network science. Introducing variables more closely related to bottom line performance metrics would be relevant to practitioners.

**Conclusion**

To affect data-driven change, organizations should do more to identify potential pain-points before they arise. Because data-driven change is not just technologically complex, but complex as a social process, well-intended strategic resource decisions can have long-term unintended consequences. Organizations should do more to not just claim a cultural change, but also explore ways to assess analytic efficacy.

This can be done through a data-driven culture audit which would include evaluating the social dynamics around analytic units in concert with a traditional organizational view. Coupling this with a resource analysis, value can be added by assessing the feasibility of data-driven change factoring in the presence of survivalistic overprotectionism and analytic facilitation.

As opposed to conceptualizing the achievement of data-driven change as something
occurring at some future point in time, the MUD suggests that deviation is unintended and also therefore unavoidable. Calculating the return on investment of analytics changes when factoring in the organizational behavior challenges that arise from too much reporting being published—a form of ineffective analytics as the data showed.

Finally, the MUD also predicts that high level executives tasked with making strategic resource decisions may have a higher probability of being duped into believing that data-driven change is happening, when in reality, unnecessary competition is causing actors to become overprotective and use data to inform their own narrative. Questions addressing what degree current data tools being utilized in an organization then becomes important, particularly in relation to some benchmark value.

Organizations should do more not just to determine what effective analytic usage should be, but also to track usage and adoption in line with an intended value—the ideal path. Although just a pilot study, the factor and regression analysis produced a significant result that warrants the need for further exploration into report usage. Knowledge transfer is uniquely challenging in hospitality gaming due to the day-to-day demands of the operation. In this environment, it may be easy to get caught up in the promise of data-driven change without completely understanding the potential ramifications and the complexity of task in achieving this kind of change.

Those who are less afraid of the nuts and bolts of data-driven solutions possess analytic facilitation, which is theorized to be important to the formation and strengthening of ABs. These bonds are critical to data-driven change and they are not visible when looking at a traditional organizational chart. They become more apparent when considering the interactions involved in facilitating analytical change among network actors, regardless of their formal power. This is because data-driven change at the interaction level requires a level of trust whereby the receiver of the analytic is also the decision maker, but does not possess the specialized knowledge of the analytic sender. The MUD predicts that as survivalistic overprotectionism worsens, the ability to develop and strengthen ABs becomes harder.

Scholars have attributed the difficulty of data-driven change to cultural and other generic
factors but these explanations fail to identify the root issues at an interaction level. The Model of Unintended Deviation (MUD) is a step forward from existing theories on the difficulties of change management. Although it can be granted that change remains more complicated than might be expected (Bergh & Fairbank, 2002), it is maintained that MUD succeeds in providing a cleaner explanation than prevailing theories. It also may seem that the MUD concerns only a small group of academics and analytically inclined practitioners, but it should in fact concern anyone who cares about better decision making and the efficient use of analytic resources.
Appendix A: In-Person Survey Questions

In person survey/interview

SD=Strongly Disagree; D=Disagree; N=Neither Agree nor Disagree; SA=Strongly Agree; NA=Not Applicable

Self-efficacy
1. I am very comfortable using the reporting solutions (Lin & Huang, 2008)
2. I regularly use the reports that are available to me. (Kim & Lee, 2006)
3. In general, my ability to use the reports effectively is strong. (Lin & Huang, 2008)
4. The reports are flexible to interact with (Kuo & Lee, 2011)

Information Access and Quality
5. The reports are designed to be user-friendly (Kim & Lee, 2006)
6. The reports process in a timely manner (Popovic et al., 2012)
7. The reports give me contradictory information (Popovic et al., 2012)
8. The reports are to the point and don’t have too much information (Popovic et al., 2012)

Task-Technology Fit
9. The reports provide the critical data I need that to perform my job (Kuo & Lee, 2011)
10. Using reports help me to be more productive (Kuo & Lee, 2011)
11. I can get the data that I need to do my job (Kuo & Lee, 2011)

Knowledge Sharing
12. To me sharing knowledge with others is beneficial. (Tohidinia & Mosakhani, 2010)
13. I share things I see on reports with team members. (Tohidinia & Mosakhani, 2010)
14. Employees use reports to communicate with others (Tohidinia & Mosakhani, 2010)
15. The reports are widely used (Tohidinia & Mosakhani, 2010)
16. When I learn something new about reports, I tell my colleagues about it (Tohidinia & Mosakhani, 2010)

Analytic Facilitation
17. I would combine certain data across different reports.
18. I would want to get involved in changing the report content.
19. I wish there were more training on certain reports.
20. The company makes as much information as possible available to employees (Spicer & Sadleer-Smith, 2006)

Questions adapted from:

Appendix B: Interview Protocol

Each interviewee will receive a recruitment form letter prior to the interview. Once the participant has given the initial go-ahead to participate, the interview location and time will be arranged. At this point, the interviewee will be briefed on the informed consent process prior to the interview taking place. If the participant understands the consent process and the nature of the research, the participant will then be given the option to participate or withdraw from participation. A copy of the form will also be provided to the participant for their reference. The interviewee then decides to participate in the interview by signing the informed consent form. The interview is estimated to last approximately 15-30 minutes and consists of six questions. The participant will be encouraged to ask questions if they have any concerns through the interview. The interview contains six questions total. The first two questions are designed to elicit qualitative data that supports the research problem. The third question is designed to directly test a hypothesis and provide construct validity. The fourth and fifth questions are related to interview protocol allowing the interviewee to ask questions and lend any additional insights to the study. The final question is for the purpose of snowball sampling.

The interview questions are as follows:

1. What are the skills that define an effective and an ineffective analyst?
2. Describe the relationship between the responsibility to learn more about analytics, and the responsibility to make analytics easier to understand for others.
3. Do you think data is utilized more effectively in some conversations than in others?
4. Is there anything that you feel we have not covered that you think would be pertinent to this area?
5. Do you have any questions for me?
6. Finally, is there anyone you would recommend for interviewing that would be useful to this study?

Probe questions include:

- “Tell me more”/“If you could give more detail”/“Please explain further”
- “What is an example of that?”
- “What did you mean when you said [___]?”
- “Is there any further information you would like to share that we have not covered?”
Appendix C: UNLV IRB Exempt Determination Letter

UNLV Social/Behavioral IRB - Exempt Review
Exempt Notice

DATE: April 9, 2018
TO: Brett Abarbanel, Phd
FROM: Office of Research Integrity - Human Subjects

PROTOCOL TITLE: [1120376-3] Efficacy of Data-Driven Interactions: Grounded Theory in Hospitality and Gaming Management

ACTION: DETERMINATION OF EXEMPT STATUS
EXEMPT DATE: April 9, 2018
REVIEW CATEGORY: Exemption category # 2

Thank you for your submission of Revision materials for this protocol. This memorandum is notification that the protocol referenced above has been reviewed as indicated in Federal regulatory statutes 45CFR46.101(b) and deemed exempt.

We will retain a copy of this correspondence with our records.

PLEASE NOTE:
Upon final determination of exempt status, the research team is responsible for conducting the research as stated in the exempt application reviewed by the ORI - HS and/or the IRB which shall include using the most recently submitted Informed Consent/Assent Forms (Information Sheet) and recruitment materials.

If your project involves paying research participants, it is recommended to contact Carisa Shaffer, ORI Program Coordinator at (702) 895-2794 to ensure compliance with the Policy for Incentives for Human Research Subjects.

Any changes to the application may cause this protocol to require a different level of IRB review. Should any changes need to be made, please submit a Modification Form. When the above-referenced protocol has been completed, please submit a Continuing Review/Progress Completion report to notify ORI - HS of its closure.

If you have questions, please contact the Office of Research Integrity - Human Subjects at IRB@unlv.edu or call 702-895-2794. Please include your protocol title and IRBNet ID in all correspondence.

Office of Research Integrity - Human Subjects
4505 Maryland Parkway . Box 451047 . Las Vegas, Nevada 89154-1047
(702) 895-2794 . FAX: (702) 895-0805 . IRB@unlv.edu
References


Curriculum Vitae
Sang-Mun Cho

E-mail address: consulting@sraycho.com
Website: sraycho.com

Education

University of Nevada, Las Vegas
Ph.D., Hospitality, December 2018
M.S., Hospitality Administration, August 2010
M.B.A., August 2010

University of Wisconsin, Madison
B.A., Communication Arts, August 2001