CREATING A CULTURE OF DATA-DRIVEN DECISION-MAKING

by

Kevin Rogers

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

Liberty University, School of Business

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Abstract

Researchers have consistently shown that a supportive culture is one of the most crucial success factors in the implementation of any big data solution. Creating a culture that supports data-driven decision-making is a difficult but ultimately required step in transforming an organization into one that can readily and successfully adopt business intelligence technologies. The purpose of this qualitative case study was to understand the ways in which organizations can foster a culture of smarter decision-making and accountability so that businesses can improve operational metrics and ultimately profitability. Participants identified three major themes that drive the adoption of a data-driven culture. These themes included building trust between decision-makers and their data, developing a team-driven culture, and instituting data governance and standard work processes to maintain quality of systems.

Keywords: Business intelligence, culture, decision-making, big data, machine learning

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Dr. Edward M. Moore, DBA Program Director

Dedication

I dedicate this dissertation to my wife, Leah Rogers. Your encouragement and never-ending support have never wavered. You deserve all the thanks in the world for your dependable inspiration and unquestionable love.

Acknowledgments

I would like to first acknowledge my dissertation chair, Dr. Melissa Connell, for her many hours spent critiquing this doctoral study. Dr. Connell's invaluable input helped in many ways to shape the final output of the dissertation process.

I also would like to thank my family, especially my mother, Tammy Rogers. Without her encouragement, I would not have initially embarked on the doctoral journey. Her commitment to education and support of her children has been an inspiration throughout my entire life.

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Section 1: Foundation of the Study

This qualitative case study seeks to understand the ways organizations can implement a culture of data-driven decision-making. At a high level, the research attempts to fill gaps identified by Bogdan and Lungescu (2018) and Olufemi (2019) which state that organizations are many times unable to become data-driven despite their technical abilities. The study aims to provide greater insight into these phenomena by analyzing an organization in the transportation industry in the United States. Trucking organizations provide a great backdrop for studying data-driven cultures (Alameen et al., 2016; Roth, 2016). The first section of the study includes (a) an introduction to the identified problem, (b) a justification for the study and its design, and (c) a review of the relevant literature.

Background of the Problem

Information technology (IT) resources, particularly through the use of data analysis, have been shown to have the ability to unlock additional possibilities with regard to strategic decision-making (Brynjolfsson & McElheran, 2016; Jabeen et al., 2016; Morton et al., 2018). Jabeen et al. (2016) noted the unique ability of IT to use its resources to enhance organizational capabilities, particularly when supplemented with strategic management. Morton et al. (2018) maintained that the flexibility and agility prevalent in modern IT organizations enables such groups to support business users in their decision-making. Brynjolfsson and McElheran (2016) found that the preceding decade saw unprecedented growth in data-driven decision-making (DDD), with use cases nearly tripling in the manufacturing industry. The unlimited ways in which data can be utilized in an organization signifies the importance of IT as a service provider and describes the ways in which IT professionals can contribute to organizational success in a meaningful way (Ylijoki & Porras, 2016). To successfully disseminate information to all parts of the business for mass consumption, the organization's culture must be supportive in nature. Garcia-Perez (2018) and Halaweh and El Massry (2015) explained that for such analytical processes to return fruitful results, a data-driven culture must be part of the organization's repertoire.

Trucking organizations often have difficulty optimizing freight networks despite an abundance of software packages and mathematical algorithms purporting to increase utilization through better routing and lane design (Alameen et al., 2016; Roth, 2016). Opportunities promoting network optimization are prevalent in trucking, with most packages allowing a variety of configurations and customizations (Demirova, 2017; Heilig et al., 2017; Parra-Romero et al., 2017; Prokudin et al., 2018). Genetic algorithms and other machine learning functions can help optimize freight networks using specific requirements set forth by organizations (Chai et al., 2017; Parra-Romero et al., 2017).

When discussing the capabilities of organizations in the analytics space, the term data maturity is often used (Cech et al., 2018; Farah, 2017). Researchers use data maturity to describe the abilities of organizations to (a) collect, (b) store, and (c) report on information, as well as implement solutions from both technological and process-based perspectives (Chen & Nath, 2018). Cech et al. (2018) provided a data competence maturity model (DCMM) that classifies data models as (a) descriptive, (b) diagnostic, (c) predictive, or (d) prescriptive. Each level requires increasingly complex technological and culture-based capabilities (Cech et al., 2018). Farah (2017) elaborated that for organizations to claim maturity with respect to their data initiatives, insights must provide value to the company. Data maturity often indicates an ability to make better decisions that increase competitiveness (Chen & Nath, 2018). According to Bogdan and Lungescu (2018), organizations cannot elicit value from data (and thus claim maturity) without widespread adoption of data-driven decision-making, a phenomenon that requires a supportive culture.

Despite the abundance of literature suggesting that advanced analytics presents great advantages for companies, many are unable to execute due to the inability to responsibly create a culture supporting data maturity (Olufemi, 2019). Mikalef et al. (2018) discovered that for organizations to successfully implement a big data solution, they must trust insights provided by data analysts and turn such insights into significant, meaningful actions. As Zeleti and Ojo (2017) explained, such insights and their derivative actions must generate some sort of value for the company. Insights without accompanying action or value are meaningless (Zeleti & Ojo, 2017).

Problem Statement

The general problem to be addressed is the inability of organizations to implement a smarter, data-driven culture despite technical capabilities in advanced analytics, resulting in a loss of potential revenue and lack of competitive advantage (Bogdan & Lungescu, 2018; Galbraith, 2014; Grover et al., 2018; Olufemi, 2019). Many organizations have difficulty transforming organizational culture into one that supports the use of data to drive decision-making (Olufemi, 2019). Galbraith (2014) asserted that organizational leaders have particular difficulty letting go of decision-making power in favor of data-driven decision-making. Bogdan and Lungescu (2018) confirmed that strategic business managers are still resistant to the adoption of big data techniques. Such researchers identify the lack of generation of a data-driven culture as a major stumbling block for organizations and flag this problem to be addressed in future studies (Bogdan & Lungescu, 2018; Galbraith, 2014). According to Grover et al. (2018), many organizations struggle with providing data scientists the support necessary for adequately producing analytical outputs. The specific problem to be addressed is the inability of trucking organizations in the southern region of the United States to create data-driven cultures of productivity and accountability, resulting in diminished operational metrics.

Purpose Statement

The purpose of this qualitative case study was to add to the existing body of knowledge and improve the understanding of a data-driven culture transformation by analyzing the ways in which organizations implement data-driven strategies. Researchers claim that if such processes can be understood and replicated, organizations can create data models and implement new technologies that can support productivity and improve performance (Garcia-Perez, 2018; Halaweh & El Massry, 2015). For the purpose of this study, a qualitative methodology was utilized. Because the intent was to understand the essence of the experience, flexible qualitative methodologies were preferred (Guillen, 2019).

A case study was used, limiting the participants to a single organization; considerations were made to ensure that results are transferable to other organizations of similar size, consistent with the assertions of Lincoln and Guba (1985). In particular, Lincoln and Guba’s (1985) concept of thick description was used to establish the context surrounding interviews; this ensured that readers can understand the insights gained from data and determine whether these conclusions are transferable. The study was intended to explore the processes by which an organization fosters a culture of accountability and productivity. The research worked to understand how a business can replace faulty, human-centric decision processes with more reliable and consistent technological and mathematics-based algorithms. The focus of the study was on a single organization working to instill a data-driven environment. The organization’s goals of creating a data-driven culture, as well as to replace decision-making power with smarter processes, were in alignment with the stated goals and research questions of interest in this study. The generalized problem was investigated through a detailed review of employee experiences at USA Truck, a publicly traded Arkansas-based transportation and logistics organization.

Nature of the Study

The selected form of research was a qualitative case study. Such a qualitative design supported the study's objectives of understanding the ways in which a data-driven culture can be instilled in a mid-size organization. Observing and conducting qualitative research alongside IT professionals and business practitioners supported the need for understanding how organizations can overcome the challenges associated with adopting a data-driven culture (Grover et al., 2018; Olufemi, 2019). Researchers overwhelmingly and consistently show that the adoption of big data analytics in business has a positive influence on firm performance (Bajari et al., 2019; Muller et al., 2018; Popovic et al., 2018). Studies frequently indicate that business intelligence practices can support non-financial operational metrics as well, having an indirect but nevertheless critical role in influencing performance (Lehrer et al., 2018). Despite such enthusiastic backing for business intelligence, organizations must be capable of creating a supportive culture; understanding the associated challenges is crucial for supporting future transformations and can be a significant help to businesses wishing to adopt smarter technologies (Halaweh & El Massry, 2015).

Discussion of Method

To best understand the intricacies surrounding the adoption of big data solutions, a qualitative study was most appropriate. According to Creswell and Creswell (2018), such a design allows researchers to best understand an event through the experiences of its observers and participants. The subjective role a researcher plays in the qualitative environment allows for interpretation and holistic understanding of an event or process (Stake, 2010). The nature of such interpretation is well-suited for the chosen problem to be addressed, which seeks to obtain understanding of a desired business result. Unlike quantitative methodologies, which tend to use statistical methods to objectively link measurable variables, qualitative methods can help explore the forces and events leading to a desired outcome (Creswell & Poth, 2018; Denzin & Lincoln, 1998). Since the advent of qualitative research, detractors often question its trustworthiness and usefulness, particularly because of its inherent reliance upon subjectivity (Lincoln & Guba, 1985). Lincoln and Guba (1985) outlined four dimensions that can be addressed to alleviate such concerns; special considerations were made to ensure the research is (a) credible, (b) transferable, (c) dependable, and (d) confirmable. Biases could have arisen from the employment status and career of the researcher. Consistent with the suggestions of Yin (2018), biases were addressed and validity earned by (a) obtaining a diverse set of participants, (b) engaging in participant and peer reviews, (c) asking neutral and open-ended questions, and (d) rigorously pursuing all possible options when inferences were made.

For this study, quantitative research would have been inappropriate. Quantitative research is often rooted in a positivist worldview, which maintains that the world can be described through measurable and quantifiable metrics (Creswell & Poth, 2018; Hasan, 2016; McAvoy & Butler, 2018). Such a design would have required strict objectivity and would not have allowed the researcher to become part of the study (Haviz & Maris, 2018; Kim & Donaldson, 2018). In a study intended to understand viewpoints of practitioners and participants, quantitative research would be impractical (Creswell & Poth, 2018). By comparison, qualitative research, based on a constructivist worldview, can more appropriately capture the essence of an experience (Bettoni, 2018; Dean, 2018; O’Connor et al., 2018). According to Guillen (2019), this is the primary goal of such a design. When working with participants to understand their viewpoints and experiences, qualitative research is the most appropriate form of study (Annansingh & Howell, 2016; Denzin & Lincoln, 1998; Guillen, 2019). Qualitative research, in the context of applied business research, can be used to answer exploratory and interpretive research questions (Creswell & Creswell, 2018; Korstjens & Moser, 2017; Kross & Giust, 2019).

Discussion of Design

According to Wynn and Williams (2012), case study research, under a critical realist philosophical paradigm, serves to explain the causes, in the form of structures and conditions, and interactions between such causes that lead to a given outcome. This was consistent with the study's goals of explaining the decisions and actions that must be taken to create a data-driven culture in an organization. In defining the case study research design, Creswell and Poth (2018) indicated that such studies must be enclosed by specific boundaries. By focusing on a single organization in the present day, this condition is easily satisfied; so long as researchers are careful to select an appropriate case in which to focus their study, results can be generalizable (Plumper et al., 2019). Working to understand how a process is or is not successful through interviews and observations within a contemporary context is consistent with Yin's (2018) overarching definition of a case study. This definition states that case studies function to investigate a phenomenon in a particular context and have many potential variables and sources of evidence (Yin, 2018).

Other forms of research design would not have adequately provided the understanding necessary to answer the selected research questions and sufficiently satisfy the problems to be addressed. Although a popular design for understanding events, and a serious candidate for this study, a phenomenological study seeks to understand only the meaning of a concept to research participants (Creswell & Poth, 2018). Fernandez (2017) defined phenomenological research as the combination of (a) existential, (b) modal, and (c) prejudicial explanations of an event. Whereas a phenomenological study is intended to understand the experiences of practitioners, a case study focuses more holistically on understanding an event using other forms of evidence. A grounded theory study would work to develop a theory behind a concept, forgoing any existing knowledge and requiring the participation of multiple practitioners (Wiesche et al., 2017). Grounded theory requires researchers to generate and verify theories grounded only in data collected as part of the study (Sato, 2019). For the purpose of this study, the researcher was expected to draw in part on prior research and to focus only on a single case. Grounded theory would have been an inappropriate research design to employ. The design of ethnography, as defined by Creswell and Poth (2018), was easily discounted under the terms of this research, as its goals are to conduct research bounded by a particular culture. Finally, a narrative approach would have required following an individual and his or her experiences related to a specific event, as well as the events that shaped his or her understanding of the occurrence. This approach was likened by Rooney et al. (2016) to storytelling. Because the focus of this study was on an organizational process, following a single individual would not have adequately explained the concepts of interest. For these reasons, a case study approach was the most appropriate research design for this study.

Summary of the Nature of the Study

The study took the form of a case study using a qualitative methodology. This methodology and design provided for a deep understanding of a phenomenon based on participant experiences (Creswell & Creswell, 2018; Stake, 2010). This enabled the researcher to examine the specific drivers that influence the implementation of a data-driven culture (Creswell

& Poth, 2018). Limiting the study to a single organization allowed the researcher to perform a detailed review of the processes, procedures, and experiences of a group of individuals in a way that was trustworthy and generalizable (Plumper et al., 2019). The researcher worked diligently to follow the best practices for case studies as outlined by Creswell and Poth (2018) and Yin (2018). Based on the goals of the research, a qualitative case study was the most suitable design.

Research Questions

The central research question that guided the investigation related to this study was: How can organizations transform their corporate philosophy into a data-driven culture that supports both productivity and accountability? Research questions included: (a) what constitutes a data-driven culture, (b) what actions can organizations take to introduce a data-driven culture, and (c) how can business strategists persuade leaders to turn over a degree of decision-making power?

Conceptual Framework

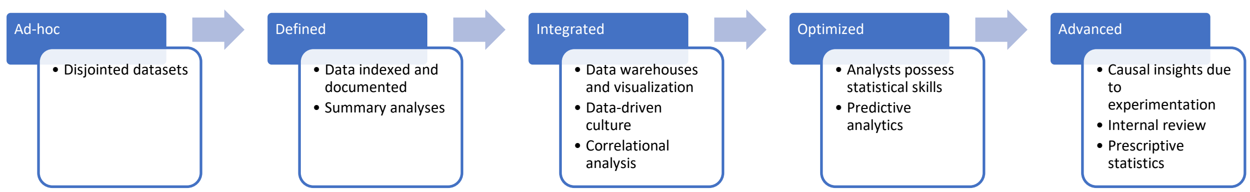
Many researchers propose data maturity models, most of which focus on the hard-skills required to implement business intelligence solutions (Cech et al., 2018; Chen & Nath, 2018; Farah, 2017). Such models often include layers explaining the technological capabilities of an organization, although they omit the soft-skills and internal marketing that must occur to successfully design and execute a big data initiative (Bogdan & Lungescu, 2018; Chen & Nath, 2018). Al Rashdi and Nair (2017) provided an overview of business intelligence maturity models, many of which include business challenges as a particular level but not as an overarching theme. Skyrius et al. (2016) proposed a model in which a culture of business intelligence feeds (a) data-driven decision-making, (b) agility, (c) maturity, (d) acceptance, and (e) adoption.

Discussion of Concept 1

Cech et al. (2018), in contrast with other researchers (Chen & Nath, 2018; Farah, 2017), understood that technological capabilities are meaningless if the company is immature with regard to data use. The researchers developed a model that aims to describe an organization's data maturity with culture as a theme permeating all other levels, as presented in Figure 1.

Figure 1

Five Levels of Data Use Maturity



Note. Adapted from "Data competence maturity: Developing data-driven decision making" by Cech et al., 2018, p. 144. Copyright 2018 by Thomas G. Cech, Trent J. Spaulding, and Joseph A. Cazier. Reprinted under Creative Commons license (see Appendix A).

For organizations in the ad hoc level, Cech et al. (2018) explain that such companies possess a variety of datasets but that they are disjointed and undocumented. A second step in the maturity model requires that data be defined; datasets must be (a) indexed, (b) documented, and (c) cataloged (Cech et al., 2018). At this stage, organizations are able to perform simple, reactive summary analyses that may help understand what problems occurred in the past and, at some level, the factors that led to particular results (Cech et al., 2018). Salmasi et al. (2016) explained that IT resources must be devoted to business intelligence solutions at this stage to manage data and build relationships with data analysts.

Discussion of Concept 2

Such resources are vital to the third stage proposed by Cech et al. (2018), who state that at an integrated level, organizations must achieve a culture of data-driven decision-making. This culture is also described by Gannon-Slater et al. (2017), who stated that such a philosophy is necessary to support business intelligence initiatives. Lawler and Joseph (2017) recognized as well that procedural factors are more important than technological capabilities when influencing the success of a business intelligence project. A multitude of other researchers concur, indicating that the integrated step as described by Cech et al. (2018) is one of the most important—and hardest to achieve—steps in the maturity process (Mesaros et al., 2016; Villamarin-Garcia & Diaz-Pinzon, 2017; Yeoh & Popovic, 2016).

At an optimized level, Cech et al. (2018) explained that organizational analysts must possess the skills necessary for conducting statistical analyses and that IT resources must be devoted to managing data. This supports the ability of an organization to conduct predictive studies using their data, providing them with the capability to use past data to predict future results (Cech et al., 2018). Mesaros et al. (2016) explained that a big data initiative that reaches the optimal level is to be enterprise-wide and must consist of (a) an enthusiastic project sponsor, (b) a matching culture, and (c) appropriate resources. The most dedicated organizations will reach the advanced stage, which Cech et al. (2018) stated consists of experimentation. At this stage, organizations may have internal committees to review results and can expect to obtain causal insights and possess algorithms that lead to prescriptive statistics (Cech et al., 2018).

Discussion of Relationships Between Concepts

The model proposed by Cech et al. (2018) featured culture as an overarching concept not limited to a single level. Instead, this model appears to place culture on a continuum, with different levels requiring different nuances within an organizational culture (Cech et al., 2018). Requiring increasingly supportive company culture in data maturity is not a new concept (Galbraith, 2014). Understanding that culture is a significant factor in a business intelligence implementation is one of its greatest success factors (Bogdan & Lungescu, 2018; Grover et al., 2018; Olufemi, 2019). Reaching the highest levels of data maturity, whether using the models proposed by Al Rashdi and Nair (2017), Cech et al. (2018), or Skyrius et al. (2016), required that organizations adopt a culture supportive of data-driven decision-making.

Summary of the Conceptual Framework

As described by Cech et al. (2018), the data maturity of an organization can be classified as (a) ad hoc, (b) defined, (c) integrated, (d) optimized, or (e) advanced. As a theme running throughout all levels of the data maturity model, especially the top three levels, organizations must work to adopt a culture that supports data-driven decision-making (Cech et al., 2018). Mudzana and Maharaj (2017) explained that the most advanced organizations make use of a variety of implementation strategies designed around particular business groups. Organizations wanting to grow their data use maturity often find themselves beginning at the ad hoc or defined stages. To become advanced, such business must complete the tasks set-forth in models proposed by researchers such as Al Rashdi and Nair (2017), Cech et al. (2018), and Skyrius et al. (2016).

Definition of Terms

The following are a list of key terms that may not be readily apparent to readers. Such terms will be used frequently throughout the study. In most cases, participants should already have a good understanding of each term, although some participants may need guidance understanding some specific meanings behind words or phrases.

Artificial intelligence (AI): The ability of a machine to flexibly (a) observe, (b) interpret, (c) understand, and (d) learn from external inputs with the end goal of applying machine knowledge to work toward a specific desired output (Haenlein & Kaplan, 2019; Kaplan & Haenlein, 2019).

Big data: Large and complex datasets that require significant resources to consume but contain valuable information including (a) trends, (b) correlations, and (c) causal insights (Grable & Lyons, 2018).

Business intelligence (BI): A field of information technology that uses (a) data collection, (b) transformation, and (c) various forms of analysis to obtain insights that can help managers and employees make decisions at all levels of the organization (Chen et al., 2012; Pappas et al., 2018).

Data maturity: The ability of an organization to (a) collect, (b) store, (c) transform, and (d) report on data, as well as its ability to build processes mandating data-driven decision-making (Cech et al., 2018; Chen & Nath, 2018; Farah, 2017).

Data mining: The process by which data are (a) located, (b) indexed, and (c) extracted from a big data environment, as well as obtaining a cursory understanding of its contents (Barua & Mondal, 2019).

Data Science: A field of information technology that curates data-sets and filters big data environments through relevant business processes and computer systems to obtain actionable insights (Berman et al., 2018; Maxwell et al., 2018).

Descriptive statistics: A form of business analytics that uses data to explain events that occurred in the past (Wixom et al., 2014).

Machine learning: A complex, iterative process using statistics and computer science to generate and regenerate statistical models with the goal of explaining the behavior of data (de Saint Laurent, 2018).

Predictive statistics: A form of business analytics that uses data to predict events that may happen in the future (Wixom et al., 2014).

Prescriptive statistics: An advanced form of business analytics that uses data to make decisions regarding what actions should be taken in the future to achieve a desired result (Wixom et al., 2014).

Assumptions, Limitations, and Delimitations

Assumptions

The research conducted as part of this study was driven by four important assumptions. First, the assumption was made that culture is an important aspect of an organization's ability to implement solutions supporting data-driven decision-making. This assumption was based in part on the research conducted by Bogdan and Lungescu (2018), Garcia-Perez (2018), and Halaweh and El Massry (2015), and their accompanying conclusions. For the purpose of this study, it was assumed that company culture is a vital component of the success of a big data solution. To mitigate any potential risks associated with this assumption, the researcher asked questions to determine if the success or failure of a big data implementation is owed in part to company culture. The results of such questions informed the ultimate conclusions drawn at the end of the study.

The second major assumption was that an organization working toward becoming data-driven includes such an endeavor in their primary organizational strategy. Calof et al. (2017) explained that becoming data-driven is a strategic decision. Without such a goal, participants will not have been able to provide meaningful insights into their experiences implementing an enterprise-wide business intelligence system. To prevent this assumption from negatively impacting the integrity of the study, the researcher ensured that the chosen organization possessed the clear and documented goal of becoming data-driven. This ensured that the organization of interest had a firm commitment to reasonably attempting a big data implementation.

A follow-up (third) assumption involved an organization's technical abilities. Because the focus of the study was on implementing a culture of data-driven decision-making, it was assumed that organizations have the capabilities to execute an implementation from a technical perspective. Alameen et al. (2016) and Roth (2016) each asserted that businesses, particularly trucking organizations, frequently possess technical capabilities. Such organizations are often unable to execute due to problems with their corporate culture (Alameen et al., 2016; Roth, 2016). To control this potential risk, the organization of interest was first evaluated to ensure that the company employed staff with the skills to implement a typical business intelligence solution. Alternatively, the researcher ensured that the company possessed the resources necessary to outsource the development of a business intelligence solution.

A fourth and final assumption centered on the ability of the researcher to draw conclusions based on the results of the case study. Due to the nature of the study being a single qualitative case study, it was assumed that the actions taken by a single trucking organization can provide insights generalizable beyond such an organization. Specifically, results were assumed to be generalizable to organizations of similar size. Without such an assumption, conclusions would have served only to explain the behavior and results observed in a single business. This is a danger observed by Lincoln and Guba (1985). According to their model, researchers can best promote trustworthiness in their studies by ensuring (a) credibility, (b) transferability, (c) dependability, and (d) confirmability (Lincoln & Guba, 1985). To mitigate the significant risks associated with this assumption, the researcher pursued multiple validation techniques, including (a) thick description, (b) triangulation, and (c) participant and peer reviews, consistent with the suggestions of Creswell and Creswell (2018) and Lincoln and Guba (1985). In particular, triangulation served to support analysis from a variety of different, diverse perspectives, while thick description supported generalizability by offering the context in which data will be observed (Creswell & Creswell, 2018). These strategies supported generalizability toward, at a minimum, organizations of similar sizes.

Limitations

Three primary limitations were identified within the design of this study. The first two limitations were related to the participants chosen to take part in the case study. The first limitation was rooted in a potential lack of experience in participants. Despite some participants possessing extensive and unique knowledge regarding the topic of interest, others may have had more limited or second-hand knowledge. Such limitations were considered when performing analysis and eliciting results from coded interviews.

A second limitation arose due to participants potentially becoming unexpectedly unavailable. Although not anticipated, the possibility existed that participants would cease employment with the host organization and become unavailable for interviews or administrative tasks regarding the study. It was highly unlikely that a large percentage of participating individuals would have been affected by this limitation. To prevent this limitation from threatening the study, the researcher attempted to interview several individuals beyond the point of saturation. This protected the study from any unexpected turnover within the participating organization.

A final limitation existed due to the nature of the study. Because the chosen research methodology was a qualitative case study, a degree of subjectivity was expected. This was because of a generalized case study's dependence on researcher involvement and the researcher's observations of a phenomenon through the lens of their own experiences (Creswell & Poth, 2018; Denzin & Lincoln, 1998; Kim & Donaldson, 2018; Yin, 2018). Steps were taken over the course of the study to reasonably ensure that areas of potential bias are eliminated. These steps were taken when interviewing participating individuals and when analyzing the collected data.

Delimitations

To delimit the scope of the study and provide concrete bounds for what is and is not included, four governing rules were utilized. First, the research was bounded to a single organization. This is consistent with a typical case study design, as defined by Yin (2018). Although the results of the study were anticipated to be in some part generalizable, the nature of focusing on a single organization suggested that the results would be useful only at the single organizational level. To improve the trustworthiness of the research, efforts were made to increase (a) credibility, (b) transferability, (c) dependability, and (d) confirmability, consistent with Lincoln and Guba’s (1985) model of trustworthiness.

A second delimiter involved focusing only on the culture behind data-driven decision-making. This meant that the technical requirements necessary for implementing a big data solution would not be discussed as part of the study. Exceptions occurred when ensuring that an organization possessed such capabilities. All other dimensions of a business intelligence solution were considered out of the scope of this study. Consideration was given to controlling for any potential confounding forces.

As a consequence of the second delimiter, the study was not limited to only the information technology department. As a third delimiter, the study included participants from many different areas of the organization. Such departments included (a) information technology, (b) reporting, (c) operations, and (d) executive leadership. This allowed the researcher to access a diverse set of individuals with the goal of reaching a point of saturation. Considering a diverse set of departments resulted in obtaining multiple perspectives as well as the processes embedded in each department that could affect the success of a business intelligence solution.

Finally, the fourth delimiter concerned the scope of the phrase data maturity and what was and was not considered part of a data maturity model. For the purposes of this qualitative case study, interviews and research were bounded by the model proposed by Cech et al. (2018). Their model includes the (a) ad hoc, (b) defined, (c) integrated, (d) optimized, and (e) advanced levels. According to the researchers, the three most mature layers require a matching company culture. Questions and interviews in this research study were designed within the bounds of this model.

Significance of the Study

This study serves to provide researchers and practitioners with a better understanding of the forces required to create a culture that supports data-driven decision-making. The research focused on a single organization to explain gaps that exist in the current body of research and supplement or augment insights found in related research. Such a study has deep-rooted origins in Biblical teachings, especially when viewed in the context of technological innovation (Giffone, 2019; Kirkpatrick, 2019). This study has strong implications for the field of strategic management and can radically change the way organizations approach implementing strategic plans (Ahmadi et al., 2016; Jabeen et al., 2016; Thamir & Poulis, 2015). Using a data-driven approach to strategic decision-making, particularly when encouraged by a supportive organizational culture, can help organizations become more competitive in the marketplace (Morton et al., 2018; Ylijoki & Porras, 2016).

Reduction of Gaps

The research study contributes to the understanding of the general problem of organizational inability to foster a culture of data-driven decision-making (Bogdan & Lungescu, 2018; Galbraith, 2014; Grover et al., 2018; Olufemi, 2019). This was studied through the specific problem of trucking companies being unable to implement big data solutions that can aid with operational decision-making (Alameen et al., 2016; Chai et al., 2017; Parra-Romero et al., 2017; Roth, 2016). The qualitative case study extends the current literature to explain the ways in which companies can (a) design, (b) implement, and (c) reap the benefits of a data-driven culture. The study does so by analyzing the strategies companies employ and determining what actions contribute to the successful implementation of a data-driven culture.

Academics and practitioners should have a better understanding of the processes and actions necessary for implementing a data-driven culture. According to Garcia-Perez (2018) and Halaweh and El Massry (2015), individuals and businesses that understand how to foster such a culture are empowered to improve organizational performance through new technology and analyses. The study was intended to focus on understanding what activities are needed to transform an organization's culture, as well as to understand the associated benefits and risks. Understanding such dynamics can help guide future practitioners, particularly when working to improve data maturity (Farah, 2017; Olufemi, 2019). Improvements in data maturity often lead to improved operational metrics (Cech et al., 2018; Skyrius et al., 2016).

In the transportation industry, many problems exist that are primed for improvement using big data solutions; such problems typically involve improving asset utilization (Alameen et al., 2016; Chai et al., 2017; Demirova, 2017; Heilig et al., 2017; Parra-Romero et al., 2017; Prokudin et al., 2018; Roth, 2016). Although many opportunities exist for transportation organizations to improve data maturity, organizations do not often trust decisions made through non-empirical methodologies, a critical component of a successful data solution implementation (Bogdan & Lungescu, 2018; Galbraith, 2014; Mikalef et al., 2018). As a result of this study, organizations are able to better understand the actions necessary to promote a culture of data-driven decision-making, necessarily indicating that insight can be provided into the ways executives and decision-makers can be persuaded to trust mathematical and technological algorithms. This trust is an important part of each of the data maturity models, particularly the integrated level proposed by Cech et al. (2018) as well as the models set forth by Al Rashdi and Nair (2017) and Skyrius et al. (2016).

Implications for Biblical Integration

Technology and a culture of technical innovation have been employed by humans since creation to help mankind reach its goals (Tennie et al., 2017; Vella, 2016). Innovation is not itself an unbiblical construct: from the very beginning of time, in Genesis 1, God created the entire universe and repeatedly saw that the things created were good. As beings made in the image of God, humans should work to cultivate as well (Keller & Alsdorf, 2012). A clear form of cultivation comes in technological advancement and the use of resources in innovative ways to further one's goals.

However, using technology as a means to an end can be dangerous, particularly if such an end is unrighteous or if the means are done so in an immoral or unethical manner (Giffone, 2019; Kirkpatrick, 2019). Even in Genesis, humanity had developed methods to build cities and towers. In building the Tower of Babel, the people said "Come, let us build ourselves a city and a tower with its top in the heavens, and let us make a name for ourselves" (Genesis 11:4, ESV, p. 8). This self-serving application of technological knowledge was met with swift judgment and punishment from God. However, innovative capabilities can be used for righteous purposes as well (Giffone, 2019; Kirkpatrick, 2019. The book of Nehemiah features one of the most ambitious construction projects of the Bible and is notable for detailing the great lengths to which the people of Jerusalem had to go to rebuild and protect their city. Nehemiah 2:18 states, "And they said, 'Let us rise up and build.' So they strengthened their hands for the good work" (ESV, p. 399). In applying technological knowledge to a noble and worthy cause, Nehemiah and the people of Jerusalem were looked upon favorably. Ultimately, the use of technology in any setting can be a righteous and holy endeavor, so long as its application and results are done for righteous and holy purposes (Giffone, 2019). This is in keeping with 1 Corinthians 10:31, which states that "whether you eat or drink, or whatever you do, do all to the glory of God" (ESV, p. 958).

As in all forms of work, employees must ensure that they are performing to the best of their ability (Keller & Alsdorf, 2012). This is commanded clearly in the Bible when Paul writes, "Whatever you do, work heartily, as for the Lord and not for men" (Colossians 3:23, ESV, p. 985). Jesus stated in Luke 14:28 that workers should always plan ahead and understand their goals before beginning work: "For which of you, desiring to build a tower, does not first sit down and count the cost, whether he has enough to complete it" (ESV, p. 874). Organizations should plan ahead when implementing a business intelligence solution and ensure that their applications and intentions are holy and righteous (Kirkpatrick, 2019). Instituting a culture of data-driven decision-making is a great step toward improving organizational metrics (Brynjolfsson & McElheran, 2016; Jabeen et al., 2016; Morton et al., 2018). However, an important aspect of such a culture should stipulate that insights are used only for noble purposes.

Relationship to Field of Study

The cultivation of a culture of data-driven decision-making has deep ties to the strategic management field (Ahmadi et al., 2016; Jabeen et al., 2016; Thamir & Poulis, 2015). IT resources, typically charged with maintaining and often tasked with analyzing data, can be used to supplement strategic management and enable better decision-making company-wide (Jabeen et al., 2016). Technological capabilities and their accompanying applications can (a) improve operational results, (b) enhance competitive advantage, and (c) increase profitability, so long as organizations have a supportive company culture (Ahmadi et al., 2016; Garcia-Perez, 2018; Halaweh & El Massry, 2015; Morton et al., 2018; Thamir & Poulis, 2015; Ylijoki & Porras, 2016). Calof et al. (2017) supported this conclusion, explaining that business intelligence must be an organizational endeavor and that transforming organizational culture is a function of strategic management. Kimble and Milolidakis (2015) concurred, maintaining that culture is important and that workers and decision-makers must understand big data to appropriately act upon its insights. The study worked to increase knowledge and understanding of cultivating a supportive culture; developing and implementing a chosen culture is one of the chief goals of a strategic manager (Farrell, 2018).

Summary of the Significance of the Study

The general, guiding purpose of this research study was to further understand the specific actions organizations can take to advance data maturity and improve organizational decision-making. Ultimately, such understanding led to increased operational performance. The specific problem of a trucking organization being unable to implement a data-driven culture is sufficiently generalizable to a wider audience of those hoping to transform culture in mid-sized organizations. For these reasons, this study has a noticeable impact on the IT and reporting arms of mid-sized organizations, especially those in the transportation industry.

A Review of the Professional and Academic Literature

Understanding the current outstanding literature regarding cultures of data-driven decision-making is important when performing academic research in this field. Literature can be divided into three logical segments, including (a) decision-making in business, (b) business intelligence and data maturity, and (c) culture transformation and characteristics of cultures of data-driven decision-making. Understanding the way leaders and employees make decisions and how business intelligence solutions support such choices is a key first step in the research process (Cao, 2017; Gauzelina & Bentza, 2017; Pranjic, 2018; Reymen et al., 2017; Ward et al., 2019). Furthermore, researchers must comprehend the possibilities technology offers and appreciate the importance of data maturity (Cech et al., 2018). Finally, knowing the process of culture transformation, as well as the specific characteristics comprising a culture of data-driven decision-making, is key to researchers operating in this field (Akaegbu & Usoro, 2017; Argenti, 2017; Gannon-Slater et al., 2017). A review of the literature reveals significant work in these segments and demonstrated the need for further research to satisfy the central research questions.

Decision-Making in Business

In the business environment, (a) strategic managers, (b) leaders, and (c) employees must make choices every day (Cronje et al., 2017; Dezfouli et al., 2019). These decisions range from a large number of operational decisions, each by itself low-impact, to a small number of highly visible and significant choices (Basic & Aleksic, 2018). Because of their importance in forming parts of larger forces, small decisions must be aligned with the strategic objectives of an organization (Mendes et al., 2018; Nikeriasova et al., 2016; Schneckenberg et al., 2017; Weiner et al., 2015). From organizational leaders to front-line employees, all decision-makers have difficulty overcoming emotions and cognitive biases that may impact their decision-making abilities (Bucurean, 2018; Otuteye & Siddiquee, 2015). In all cases, decision-makers must also overcome the challenges associated with relinquishing power to technologies that can serve as decision support tools (Bogdan & Lungescu, 2018; Galbraith, 2014; Grover et al., 2018) and understand that such technologies are intended to be used as tools, not perfect replacements for intuition (Cao, 2017). Decision-making is a consistently prevalent and complex function of the human mind that can be supplemented by technology to make (a) smarter, (b) faster, and (c) more informed decisions (Gauzelina & Bentza, 2017; Pranjic, 2018; Reymen et al., 2017; Ward et al., 2019).

Decision Models. In a generalized sense, complex decisions are widely prevalent and inherent in the human experience (Dezfouli et al., 2019). Basic and Aleksic (2018) described decision-making as a method by which an (a) individual, (b) group, or (c) entity chooses between several paths to achieve a desired output. Many researchers explain that decisions are often made with respect to multiple dimensions and influences (Cronje et al., 2017; Espinoza et al., 2019). This implies that decision-makers must consider various perspectives and aspects of a problem before making a decision (Cronje et al., 2017; Espinoza et al., 2019). According to Cronje et al. (2017), decisions can be influenced through (a) finances, (b) morals and ethics, (c) emotions, or (d) pressure from outside forces. The researchers also determine that decisions are often made due to changes in the competitive environment (Cronje et al., 2017). Espinoza et al. (2019) explained that decisions can be made with respect to six dimensions, including (a) political factors, (b) economic pressures, (c) social influences, (d) technological opportunities, (e) environmental reasons, and (f) legal requirements. When business decision-makers choose between various options, they may use such a tool to help guide and inform their selections (Espinoza et al., 2019).

Decision-makers can use established methodologies to improve their decision-making ability and the quality of their choices (Abdallah et al., 2019; Basic & Aleksic, 2018; Rabin & Bazerman, 2019; Sandhawalia & Dalcher, 2015). Such methodologies may apply to non-human decision-makers just as well as they do to human decision-makers (Abdallah et al., 2019; Basic & Aleksic, 2018; Rabin & Bazerman, 2019; Sandhawalia & Dalcher, 2015). Sandhawalia and Dalcher (2015) explained that the best decisions make use of both tacit and explicit knowledge. Explicit knowledge refers to structured, documented knowledge, while tacit knowledge refers to the undocumented and experiential learning that is more difficult to transfer (Davila et al., 2019). According to Basic and Aleksic (2018), business decisions can be improved when decision-makers have the proper education and motivations and are willing to take responsibility for their choices, as well as when decision power is appropriately distributed throughout an organization. Rabin and Bazerman (2019) conveyed the importance of remaining consistent in decision-making and caution against being too risk averse. Such safeguards may help prevent poor, ill-advised decisions (Rabin & Bazerman, 2019).

Abdallah et al. (2019) provided four primary steps inherent in any decision, explaining that innovation and cognition can provide a significant improvement over existing decision-making abilities. Such principles apply whether a choice is made by (a) a machine, (b) individual, or (c) group of individuals. The first step in their model involves observing and perceiving data from the surrounding environment. Decision-makers receive inputs, which are then used in the decision-making process (Abdallah et al., 2019). The second step, as proposed by these researchers, consists of the processing of the inputs. This involves understanding and breaking down the inputs into manageable units of knowledge. The decision-maker's next step, according to the researchers, is to prioritize choices based on the inputs and their transformations, while the fourth and final step requires a decision to be made.

Decision-makers are not always necessarily human: computers and technology are increasingly being used to make difficult decisions in place of human decision-makers (Gauzelina & Bentza, 2017; Pranjic, 2018; Reymen et al., 2017; Ward et al., 2019). Such technology is the result of organizations looking for ways to use information collected in databases to take decision-making out of the hands of fallible humans (Gauzelina & Bentza, 2017; Pranjic, 2018). In this way, businesses can satisfy the concerns of Rabin and Bazerman (2019), which encourage consistency in decision-making. The use of data to drive decision-making can also prevent subjectivity from tainting the quality of decisions, as mentioned by Basic and Aleksic (2018). The use of data in making decisions often uses only explicit knowledge as recorded in a database; to satisfy the requirements for inclusion of tacit and explicit knowledge as defined by Sandhawalia and Dalcher (2015), technology organizations must find ways to improve their utilization of unstructured or even undocumented knowledge. Advanced technologies such as artificial intelligence can be employed to replace human decision-makers (Shrestha et al., 2019), although such technologies require significant organizational backing (Bogdan & Lungescu, 2018).

Micro-Decisions Support Strategic Decisions. Tools that aid in decision-making, particularly those that use more advanced technologies, are not limited to any one type of decision-making or decision-making at any one level (Weiner et al., 2015). According to Schneckenberg et al. (2017), decision-making strategies, regardless of whether or not they are aided by technology, are part of larger organizational initiatives. Decisions are made at all levels of the organization, whether they be (a) operational, (b) tactical, or (c) strategic. Although decisions are most impactful at the highest, strategic level and such decisions require the greatest amount of responsibility, strategic choices must be supported by tactical and operational decisions (Basic & Aleksic, 2018). This indicates that operational decisions from the front-line employees will, in an aggregated form, influence the direction of strategic metrics (Mendes et al., 2018; Weiner et al., 2015). Nikeriasova et al. (2016) concurred, writing that one of the ways organizational strategies are executed is through operational-level decision-making and activities.

Operational-level micro-decisions should not be made in a vacuum with disregard to the external environment (Darabos-Longin, 2018; Ivancic et al., 2017). In the modern business environment, with external changes being made at a rapid pace, internal decision-making must be quick to respond (Darabos-Longin, 2018; Kitchens et al., 2018). As a result, firm agility is an important and necessary quality of business organizations (Darabos-Longin, 2018; Kitchens et al., 2018; Park et al., 2017). Such agility is achievable in part through technological improvements, including business intelligence solutions and big data initiatives (Kitchens et al., 2018). Park et al. (2017) also noted the importance of a supportive infrastructure that encourages communication and collaboration. Such agility is absolutely necessary due to unpredictable and quickly-changing external conditions and can improve the execution of an organizational strategy (Ivancic et al., 2017). Micro-decisions supportive of an overall strategy but at odds with the external environment can cause harm to an organization (Ivancic et al., 2017).

Modern organizations often plan to use data-driven initiatives to support decision-making at various levels within their businesses (Gauzelina & Bentza, 2017; Pranjic, 2018; Reymen et al., 2017; Ward et al., 2019). Weiner et al. (2015) provided a model for this approach, explaining that reporting and business intelligence solutions must consider the impact decisions will have on other levels of the organization. Mendes et al. (2018) maintained that data can be used to support decisions at any level of an organization to promote innovation or achieve or sustain a competitive advantage. Researchers consistently explain that strategic metrics are explainable by operational data and decisions, indicating that (a) operational, (b) tactical, and (c) strategic decisions form a sort of hierarchy that must be in sync (Mendes et al., 2018; Weiner et al., 2015). When working to implement a culture of data-driven decision-making, organizational leaders must ensure that their initiatives are aligned with the principles governing operational and strategic management (Mendes et al., 2018; Weiner et al., 2015).

Emotions and Cognitive Biases. Decision-making is often at the mercy of a decision-maker's moods and emotions, as well as their cognitive abilities (Bucurean, 2018; Otuteye & Siddiquee, 2015). Such factors can affect the quality of choices when allowed to influence decision-makers, whether in the individual or group setting (Chong et al., 2018; Paraboni et al., 2019). Bucurean (2018) explained that positive emotions have a positive influence over a decision-maker's cognitive ability to understand inputs, though they have a negative impact on the speed by which a decision can be made. Bucurean (2018) also stated that positive moods can lead to more irrational decision-making based on emotion and concludes that decision-makers should work to improve their emotional intelligence. Allowing decisions to be made by a group does not necessarily dilute the effects of moods and emotions; personalities and moods of individuals within a group can still have significant effects on the quality of decisions (Chong et al., 2018). Groups are also more prone to bad decisions regarding sunk costs and are less likely to steer away from unprofitable projects (Paraboni et al., 2019). Iigaya et al. (2016) found that when individuals have negative emotions, they become more risk averse, explaining that such effects occur even when individuals are unaware of their negative moods. Such influences can be mitigated or avoided entirely when decisions are made using data-driven tools (Gauzelina & Bentza, 2017; Pranjic, 2018; Reymen et al., 2017; Ward et al., 2019).

Cognitive biases pose a significant problem in business management, particularly because such biases impair a decision-maker's judgment and lead to flawed decisions with potentially long-term impacts (Otuteye & Siddiquee, 2015). Such biases refer to situations when managers and decision-makers process information incorrectly, leading to faulty decisions (Otuteye & Siddiquee, 2015). Montibeller and Winterfeldt (2015) explained that cognitive biases arise from improper mental processes and can also be a result of motivational biases. These biases occur when decisions are rooted in external pressures or self-interest (Montibeller & Winterfeldt, 2015). As with moods and emotions, business intelligence technologies and data-driven decision-making tools can help bridge gaps in decision-making abilities introduced by cognitive biases (Gauzelina & Bentza, 2017; Pranjic, 2018; Reymen et al., 2017; Ward et al., 2019).

Opportunities in Transportation. In many industries, technology can be used to supplement or enhance decision-making, particularly when tools rely on expansive datasets to prescribe actions (Brynjolfsson & McElheran, 2016; Jabeen et al., 2016; Morton et al., 2018). Organizations often work to generate solutions at the cross-section between technology and business processes to automate mundane or thoughtless tasks (Demirova, 2017). When businesses want to automate iterative statistical models explaining the behavior of variables, they must engage in some form of artificial intelligence (Haenlein & Kaplan, 2019; Kaplan & Haenlein, 2019). As a subset of AI technologies, machine learning allows practitioners to let computers train themselves, an option that many organizations find particularly useful (de Saint

Laurent, 2018). These technologies are not unique to transportation, though it is important to understand their capabilities to understand what tools are best employed for improving specific problems (Brynjolfsson & McElheran, 2016; de Saint Laurent, 2018; Jabeen et al., 2016; Morton et al., 2018).

One of the most popular but difficult-to-solve problems in transportation is the traveling salesman problem (Alameen et al., 2016; Heilig et al., 2017; Roth, 2016). This problem involves determining the fastest route between a set of locations, although in the transportation industry many additional factors exist (Roth, 2016). Heilig et al. (2017) provided a wealth of other considerations, including (a) freight and driver availability, (b) traffic conditions, (c) appointment times, and (d) drive time restrictions. Alameen et al. (2016) showed that if transportation organizations can better optimize truck routing, they will be able to cut costs and reduce fuel consumption. Optimizing routing will also lead to better utilization and service (Alameen et al., 2016). Finding the most optimal route using business intelligence solutions may be resource-intensive, though these solutions may provide plans that more closely resemble an optimal path (Heilig et al., 2017).

Gansterer et al. (2017) explained that before organizations can work to optimize a route, they must determine what freight opportunities to pursue. The researchers go on to state that whether or not organizations agree to accept an opportunity is dependent on a variety of different factors, notably whether they have coverage in the region. Organizations must organize their freight availability and truck positions in such a way that (a) reduces idle time, (b) increases utilization, and (c) remains legally compliant (Vidal et al., 2016). Chai et al. (2017) introduced the concept of genetic algorithms, which allow organizations to define parameters and analyze data based on the principles of human biology and natural selection. The researchers state that this process can be used to identify the best arrangement of trucks and freight (Chai et al., 2017). Parra-Romero et al. (2017) concurred, explaining that the use of genetic algorithms can help determine the most optimal network configuration based on a series of defined parameters and boundaries.

Business intelligence solutions can be used to mitigate risks associated with unknowns (Park et al., 2016; Prokudin et al., 2018). Due to the highly unpredictable nature of the transportation industry, it may be difficult to predict (a) precise arrival times, (b) freight availability, or (c) traffic conditions (Gansterer et al., 2017; Vidal et al., 2016). Prokudin et al. (2018) explained that solutions should be able to adapt and respond to changes in the environment. The researchers explain that, through the use of technology, organizations can frequently regenerate optimal driver plans through a process known as itinerary optimization (Prokudin et al., 2018). Hughes-Cromwick and Coronado (2019) suggested that transportation organizations take advantage of freely available datasets, particularly those maintained by the United States government, to understand the potential roadblocks standing in the way of drivers. Park et al. (2016) found that organizations can use their own and shared datasets to predict traffic accidents and other traffic conditions to help improve utilization and promote safe driving. The transportation industry provides a rich landscape of potential applications for big data technologies, each of which aid decision-makers in making choices at all levels of an organization (Chai et al., 2017; Demirova, 2017; Heilig et al., 2017; Parra-Romero et al., 2017; Prokudin et al., 2018).

Intuition and Technological Substitution. Business leaders and decision-makers at all levels of the organization are often plagued with a degree of uncertainty (Amariei & Hamat, 2018; Fomin et al., 2016; Marewski et al., 2018; Reymen et al., 2017). This results in a forced reliance on intuition (Amariei & Hamat, 2018). Schwartz (2016) described two forms of decision-making, consisting of rational, or reason-based, and non-rational, or intuitive or emotion-based, decision-making strategies. Fomin et al. (2016) arrived at the same two classifications, although they show that intuitive decision-making is not necessarily ineffective. When key information is missing and decision-makers are unable to use logic or reason to solve a problem, they must depend on their ability to generate creative leaps (Amariei & Hamat, 2018). Reymen et al. (2017) explained that effectual decision-making, in contrast with causal logic, is a tactic used when humans must make educated guesses. Such guesses, they show, bridge the gap left by a lack of information or data (Reymen et al., 2017). Marewski et al. (2018) showed that experience and context are two aspects of an intuition-based decision, each of which are inherent in the human brain.

The biological processes inherent in intuition-based decision-making pose a unique challenge for data scientists and proponents of big data technologies (Cao, 2017). According to various researchers, decision-makers must be able to make creative leaps based on experience and context when information is missing (Amariei & Hamat, 2018; Marewski et al., 2018; Reymen et al., 2017). If information, or specifically data, is missing, data-driven decision-making technology must be able to arrive at a solution in some other way. Cao (2017) stated that data models may never be as complex and powerful as the human brain, though technological models may still achieve a degree of intuition and creativity. Researchers typically agree that big data solutions are imperfect but are an asset that can be leveraged to supplement decision-making when unknowns may exist in the environment (Cao, 2017).

Data-Driven Decision-Making. As a function of business decision-making, data-driven processes add value to the organization (Benmoussa et al., 2018; Seddon et al., 2017). For data-driven solutions to contribute their maximum potential, they must consist of a defined process, such as (a) analytics, (b) insights, (c) decisions, and (d) actions (Seddon et al., 2017). Data-driven decision-making more specifically refers in many cases to decision support; although not infallible, data-driven processes often provide support to the decision-making process and provide evidence supporting a position, but do not always make decisions themselves (Benmoussa et al., 2018). Despite the difficulty of simulating the complexities of the human brain, Benmoussa et al. (2018) argued that data scientists should work toward continuous improvement. In addition to adding organizational value, employing a data-driven strategy increases competitive advantage and can help organizations increase market share (Morton et al., 2018; Ylijoki & Porras, 2016). The rewards gained from transitioning toward a data-driven approach to decision-making pose a unique challenge for leaders and managers reluctant to release their decision-making power (Bogdan & Lungescu, 2018; Galbraith, 2014; Grover et al., 2018).

Ultimately, the purpose of introducing a culture of data-driven decision-making is to promote decision strategies rooted in scientific data-based evidence (Garcia-Perez, 2018; Halaweh & El Massry, 2015). This has the effect of transitioning decision-making power to machine-based algorithms and data models. Shrestha et al. (2019) explained that big data technologies transfer decision-making responsibilities away from humans and toward more reason-based models. This is necessary, as argued by Gauzelina and Bentza (2017) and Ward et al. (2019), because human decision-makers are often irrational and make faulty decisions based on their own biases and imperfections. All levels of the organization can benefit from a greater reliance on data-driven decision-making (Pranjic, 2018).

A healthy dependence on data-driven decision-making supports both development and execution of an organization's overall strategy (Calof et al., 2017; Levenson, 2018). Researchers overwhelmingly agree that big data solutions support strategic choices when business intelligence is part of an organization's culture (Ahmadi et al., 2016; Calof et al., 2017; Morton et al., 2018; Thamir & Poulis, 2015; Ylijoki & Porras, 2016). Levenson (2018) explained that data-driven decision-making results in improved execution of strategy through greater effectiveness. This is divided further into analytics concerning competitive advantage, or external analytics, and analytics regarding the internal organization (Levenson, 2018). As an organizational activity, the utilization of data in decision-making occupies a unique space in that it both supports strategic development and is itself a strategic initiative (Ahmadi et al., 2016; Calof et al., 2017; Jabeen et al., 2016; Thamir & Poulis, 2015).

Summary of Decision-Making in Business. Decisions are a constant reality in business and always have a direct or indirect impact on significant organizational metrics (Basic & Aleksic, 2018; Cronje et al., 2017; Dezfouli et al., 2019). Decision-makers must be careful to use the tools at their disposal to maximize the effectiveness of their decision-making abilities while preventing bias resulting from low emotional intelligence (Bucurean, 2018; Galbraith, 2014; Otuteye & Siddiquee, 2015). Technology can be used as one such tool and become the basis for decision-making in an organization (Gauzelina & Bentza, 2017; Pranjic, 2018; Reymen et al., 2017; Ward et al., 2019). For organizations to implement these tools, they must possess both the technical and cultural skills necessary to support data-driven initiatives (Halaweh & El Massry, 2015; Jabeen et al., 2016). This is the basis for data maturity, the primary method by which organizations encourage data-driven programs (Cech et al., 2018; Chen & Nath, 2018; Farah, 2017).

Business Intelligence and Data Maturity

Data science and tasks comprising business intelligence are performed primarily to improve decision-making by creating decision support tools or even replacements for human decision-makers (Morton et al., 2018; Nykanen et al., 2016; Pappas et al., 2018; Shrestha et al., 2019). This revolutionary, emerging field threatens the way organizations have traditionally operated and require a major transformation in businesses that hope to remain competitive in the marketplace (Arghir et al., 2019). Brynjolfsson and McElheran (2016) maintained that data maturity is intended to drive decision-making primarily through scientific data analysis. Such analysis can range from simple descriptive statistics to artificial intelligence and machine learning algorithms running in real-time (Brynjolfsson & McElheran, 2016; de Saint Laurent, 2018; Shrestha et al., 2019). These algorithms can even, through technology, be automated to perform operational actions within an organization (Berman et al., 2018; Haenlein & Kaplan, 2019; Kaplan & Haenlein, 2019; Zhang et al., 2018). These functions consistently lead to better and faster decisions, ultimately resulting in improved overall financial results (Arghir et al., 2019; Bajari et al., 2019; Muller et al., 2018; Popovic et al., 2018; Nykanen et al., 2016).

Researchers propose a variety of models that aim to explain the levels of maturity organizations exhibit with regard to their data usage (Al Rashdi & Nair, 2017; Cech et al., 2018; Farah, 2017; Skyrius et al., 2016; Tavallaei et al., 2015). These models often begin by describing ad-hoc analysis or a lack of planning for data-driven decision-making and progress to describing advanced, data-driven organizations (Cech et al., 2018). Al Rashdi and Nair (2017) indicated that maturity applies to several dimensions, including the technological and cultural aspects of business intelligence. Obtaining technology and appropriate human resources is an early step in improving business intelligence maturity (Chen & Nath, 2018; Ylijoki & Porras, 2016). Further steps require improvements in organizational culture and encouraging organizations to use all available resources to maximize the usefulness of their data (Gannon-Slater et al., 2017; Mikalef et al., 2018).

Business Intelligence and Decision-Making. The concepts associated with business intelligence, including (a) business analytics, (b) artificial intelligence, (c) machine learning, and (d) data modelling, are all associated with leading business leaders and employees toward better decision-making (Chen et al., 2012; Morton et al., 2018; Nykanen et al., 2016; Pappas et al., 2018). According to Arghir et al. (2019), business intelligence has a profound impact on the way users make decisions. The researchers state that business intelligence uses an organization's available historical data, as well as publicly-available data, to obtain useful and actionable insights into organizational processes and performance (Arghir et al., 2019).

The basic principles of business intelligence for decision-making are universal (Nykanen et al., 2016). The primary goals of business intelligence are to use available data to answer difficult questions and provide a decision support tool for decision-makers (Morton et al., 2018; Nykanen et al., 2016; Pappas et al., 2018). The first of these goals is the use of data as a methodology for decision-making (Nykanen et al., 2016; Pappas et al., 2018). Business intelligence solutions predict why an event or trend occurred and can also be forward-looking or predictive in nature (Pappas et al., 2018). As Nykanen et al. (2016) stated, data analysis increases knowledge about the way an organization operates within the context of both the internal and external environments, leading to more knowledgeable and informed decision-making. Arghir et al. (2019) corroborated this statement, explaining that data informs decision-makers in the form of analyzable data. Existing business intelligence technologies, built on these principles, encourage action rooted in data analysis rather than solely opinions and intuition (Brynjolfsson

& McElheran, 2016). Due to the highly technical nature of business intelligence solutions, Jabeen et al. (2016) highlighted the importance of information technology (IT) departments to the process. The second overarching business intelligence principle holds that these solutions provide a decision support tool on which business decision-makers can rely (Morton et al., 2018; Nykanen et al., 2016). Business intelligence tools drive decision-makers to quicker and more-informed choices by eliciting knowledge from available data (Nykanen et al., 2016). Morton et al. (2018) claimed that business intelligence as a decision support tool can be useful to decision-makers at all levels of the organization, ranging from operational-level employees to strategic leaders. Chen et al. (2012) explained that business intelligence technologies can provide even real-time decision support, especially at the operational level of the organization.

Business intelligence and its use in decision-making is a highly popular and prevalent initiative within organizations (Brynjolfsson & McElheran, 2016; Dukic et al., 2016; Pappas et al., 2018). Decision support tools, most rooted in at least some degree of organizational and publicly-available data, are being adopted at a rapid pace (Brynjolfsson & McElheran, 2016). Dukic et al. (2016) elaborated, explaining that modern business technologies most always contain tools that help users make data-based decisions. These technologies push business intelligence principles down to the operational level in real-time and are widely utilized in corporate environments (Chen et al., 2012; Dukic et al., 2016). Throughout the 2010s, the prevalence of data sources grew exponentially, exhibiting an unprecedented level of data collection and sharing (Pappas et al., 2018). Technologies such as (a) social media, (b) enterprise software, and (c) sensors in everyday items (e.g., smartphones, automobiles, or even kitchen appliances) record and transmit data on a constant basis, providing data analysts with a wealth of sources from which to elicit information and insight (Pappas et al., 2018). The prevalence of business intelligence technology has grown at a rapid pace and indicates that the popularity of data-driven decision-making is ever-growing (Brynjolfsson & McElheran, 2016; Pappas et al., 2018).

Researchers often address success factors related to business intelligence and its effect on organizational decision-making (Arghir et al., 2019; Chen & Nath, 2018; Kulkarni et al., 2017; Morton et al., 2018). Executive involvement in any business intelligence initiative is a leading factor in determining its success (Morton et al., 2018). Without such involvement, the researchers state, information technology organizations will be unable to support the strategic goals of the wider business (Morton et al., 2018). Kulkarni et al. (2017) provided additional detail, showing that support for business intelligence must begin at the executive level but be executed through user involvement and with the right analytical technologies. Chen and Nath (2018) indicated that even managerial opinions regarding information technology departments can positively or negatively impact a business intelligence solution aimed at affecting decision-making. The researchers go on to explain that the success of a business intelligence implementation is also dependent on (a) technological capabilities, (b) integration and support of the solution, and (c) whether or not the solution provides benefits to the organization (Chen & Nath, 2018). Arghir et al. (2019) provided additional factors, including (a) usability, (b) long-term performance results, (c) level of adoption, and (d) cost. Such factors are crucial in ensuring success of a business intelligence solution and especially its influence over decision-making across an organization (Arghir et al., 2019; Chen & Nath, 2018).

Emerging technologies indicate that future and sometimes present business intelligence solutions may not always require human interaction (de Saint Laurent, 2018; Haenlein & Kaplan, 2019; Kaplan & Haenlein, 2019; Shrestha et al., 2019). Artificial intelligence and machine learning capabilities enable machines to perform real-time (a) data processing and analysis, (b) decision-making, and (c) execution (de Saint Laurent, 2018; Shrestha et al., 2019). Shrestha et al. (2019) explained that business intelligence is no longer a simple decision support tool but a much larger phenomenon that can, to some degree, replace human decision-makers. Artificial intelligence uses complex algorithms to determine the proper path, then uses these insights to perform some action (Haenlein & Kaplan, 2019; Kaplan & Haenlein, 2019). Due to the sometimes-controversial nature of this technology, its implementation requires a momentous effort by the organization (Bogdan & Lungescu, 2018). If artificial intelligence and machine learning technologies are representative of the future of business intelligence, the dynamics between employees and decision-making will shift radically over the 2020s (de Saint Laurent, 2018; Shrestha et al., 2019).

Information Technology and Relationship to Business Intelligence. Big data solutions require the involvement of information technology departments, but such technical resources cannot by themselves implement a successful system (Halaweh & El Massry, 2015; Jabeen et al., 2016). Information technology departments, first, produce capabilities by obtaining the appropriate technologies and talent (Ylijoki & Porras, 2016). Skills in data analytics and data analytics technologies are a major determinant of business intelligence maturity (Chen & Nath, 2018). Halaweh and El Massry (2015) explained that business intelligence solutions must consist of various technical qualities, including (a) data quality and availability, (b) information technology infrastructure, (c) employees possessing the correct skill-sets, and (d) security and privacy of data. Jabeen et al. (2016) asserted that information technology can produce organizational capabilities but that other departments and particularly executive sponsors must possess a degree of technological literacy. Researchers frequently agree that, while not minimizing the degree of work required, the technical implementation of a big data solution is almost always the simplest and quickest stage (Halaweh & El Massry, 2015).

Information technology resources, by themselves, are not enough to accomplish the goals of a big data implementation (Jabeen et al., 2016). Information technology strategy must be aligned with the organizational strategy, and the department's actions must be strategically and deliberately planned (Jabeen et al., 2016; Ylijoki & Porras, 2016). Halaweh and El Massry (2015) suggested that this requires a radical shift in business models and the way leaders and employees interact with and treat data. The researchers also state that this shift begins with top management (Halaweh & El Massry, 2015; Morton et al., 2018). Although information technology resources can develop the technical solutions required to implement a business intelligence solution, business-oriented individuals must be involved to drive adoption (Ylijoki & Porras, 2016). In this way, the business can transform assets such as data warehouses or machine learning tools into actionable and programmable insights with major impacts on the organization (Ylijoki & Porras, 2019). When information technology efforts are supplemented with organizational support, especially from the management level, organizations can increase their business intelligence maturity (Chen & Nath, 2018).

History and Opportunities. Though the origins of artificial intelligence and business intelligence are relatively recent, the pace at which they have been developed can be described only as rapid (Grable & Lyons, 2018; Haenlein & Kaplan, 2019). These concepts were first described in 1942 in Isaac Asimov's *Runaround*, a short story establishing the laws of robotics (Haenlein & Kaplan, 2019). On a more practical front, Alan Turing developed machines to break German codes in the Second World War (Haenlein & Kaplan, 2019). Over the next several years, mathematicians and computer programmers worked to use technology to solve elusive problems in their respective fields (Haenlein & Kaplan, 2019). This led to the Dartmouth Summer Research Project on Artificial Intelligence in 1955, the first time the phrase "artificial intelligence" was officially used (McCarthy et al., 2006, p. 12). This event is widely considered to be a seminal occasion in the development of artificial intelligence (Haenlein & Kaplan, 2019). By the end of the 20th century and the beginning of the 21st, computer programmers and engineers had begun to develop applications and sensors that generated and stored massive amounts of data that could be consumed by business intelligence professionals (Grable & Lyons, 2018). The phrase "big data" was eventually coined by Doug Laney to describe datasets with (a) large volume, (b) high velocity, and (c) great variety (Grable & Lyons, 2018, p. 17). Big data and its use in business intelligence is a subject of research even in the late 2010s and early 2020s and is, in some circles, at risk of falling out of favor with organizations (Barua & Mondal, 2019; Wixom et al., 2014).

A major current technical issue facing big data and business intelligence for data-driven decision-making is the volume of such data and the challenges this creates with regard to data (a) storage, (b) management, (c) administration, and (d) processing (Barua & Mondal, 2019). For these reasons, many organizations are opting to move to cloud-based data storage and processing, enabling businesses to scale up and down in hardware as needed (Barua & Mondal, 2019). Due to the complexities associated with developing a business intelligence and particularly big data solution, Wixom et al. (2014) warned that popularity of big data for decision-making may experience a sharp decrease in the 2020s. A relatively recent development in the field is the ability of data scientists to use people-generated data from social media as a way to market products and services to customers at a more personal level (Gioti et al., 2018). New sources of data are constantly in development; cloud-based technologies enable data scientists and business intelligence researchers to process information quickly and relatively inexpensively (Barua & Mondal, 2019; Gioti et al., 2018; Wixom et al., 2014).

Research opportunities exist on the organizational side of business intelligence as well (de Saint Laurent, 2018; Gioti et al., 2018; Lopez-Robles et al., 2018). De Saint Laurent (2018) wrote that because artificial intelligence and machine learning are relatively new concepts, executive leadership often misinterprets results or has incorrect preconceived notions about what business intelligence is and is not. Many business executives believe that business intelligence can provide exact answers to any question they have; others may misinterpret results (de Saint Laurent, 2018). Education is required to ensure organizational leaders understand how to manage business intelligence projects and apply results appropriately (de Saint Laurent, 2018). Lopez-Robles et al. (2018) explained that contemporary research frequently tries to understand how business intelligence concepts can be applied by business leaders, particularly by studying key success factors and knowledge management. Finally, Gioti et al. (2018) introduced ethical questions, asking if any types of data are off-limits to researchers and debating the merits of unrestricted access to data.

Advantages of Business Intelligence. Researchers consistently assert that business intelligence provides a discernable advantage to a firm’s financial performance under the right circumstances (Bajari et al., 2019; Muller et al., 2018; Popovic et al., 2018). Muller et al. (2018) asserted that the active use of business intelligence solutions results in an average of 3% to 7% improvement in the productivity of an organization when the business focuses on information technology or operates in a highly competitive industry. Such results require improvements in the way organizations (a) collect, (b) store, and (c) analyze data (Bajari et al., 2019). Although increasingly large datasets eventually reach a point of diminishing returns, the acts of housing and sufficiently analyzing large amounts of data typically result in improved organizational performance (Bajari et al., 2019). According to Heller (2019), productivity can be improved through business intelligence even on the personal level. Ultimately, when organizations possess appropriate information technology capabilities and display readiness for big data solutions, advanced data analysis systems will enhance their performance (Popovic et al., 2018).

Improving a firm’s productivity is far from the only advantage of implementing a business intelligence solution. Researchers consistently argue that insights gathered from big data improve the quality and speed of decisions (Arghir et al., 2019; Brynjolfsson & McElheran, 2016; Nykanen et al., 2016). Non-human decision-makers are improved as well, with computer programs transitioning from using human-developed logic to self-learning algorithms (de Saint Laurent, 2018). This creates an interesting dynamic in which computers designed and programmed by humans can make decisions faster and sometimes more accurately than humans (Shrestha et al., 2019). Lehrer et al. (2018) explained that apart from decision-making, business intelligence improves various other organizational metrics. Service levels are increased in the cases of both business intelligence as a decision support tool and business intelligence as a decision-making tool (Lehrer et al., 2018). With advanced business intelligence solutions, organizations can (a) personalize service to the customer, (b) lower costs associated with producing a product and therefore pass savings on to the customer, and (c) increase the value of the products offered (Lehrer et al., 2018).

Business Intelligence Opportunities and Applications. As with any developing industry, the opportunities for the application of business intelligence technologies are numerous (Balina et al., 2016; Ivan, 2015; Obeidat et al., 2015; Svarre & Gaardboe, 2018). Despite widespread agreement that business intelligence applications improve organizational performance, many businesses and industries find that leaders are often unwilling to adopt business intelligence practices (Bogdan & Lungescu, 2018; Galbraith, 2014). Svarre and Gaardboe (2018) found that the majority of business intelligence users are operational employees and not necessarily leaders within their organization. Employees in many cases claim that the majority of their work is completed without the aid of business intelligence technologies (Svarre & Gaardboe, 2018). This presents a great opportunity for business intelligence professionals to expand their influence by increasing the number of users and prevalence of technology in users' daily routines (Svarre & Gaardboe, 2018).

Business intelligence users report a number of needs while business intelligence professionals suggest functionality that increases their effect on business (Balina et al., 2016; Ivan, 2015; Obeidat et al., 2015). Self-service business intelligence is a highly desirable form of data analysis, allowing users to complete analysis themselves without the need for business intelligence or analyst involvement (Balina et al., 2016; Obeidat et al., 2015). Self-service principles include (a) ease of application deployment, (b) simplicity of data models and analysis tools, and (c) low cost implementation (Balina et al., 2016). This form of business intelligence can be complimented by visualization, a function that allows users to see data in an easy-to-understand format (Obeidat et al., 2015). Ivan (2015) reminded practitioners that business leaders, accustomed to working on-the-go, are likely to want data and insights delivered in a mobile format. From a technical perspective, information technology professionals look for solutions that provide open source and cloud computing capabilities (Obeidat et al., 2015). These opportunities together provide business strategists and analysts a roadmap for innovation and indicates that decision-makers are eager, if only on the surface, to pursue business intelligence solutions (Balina et al., 2016; Ivan, 2015; Obeidat et al., 2015).

Applications of Advanced Data Science. Advanced data science techniques allow data scientists and other business professionals to elicit information from data surrounding systems and business processes, as well as to transform insights into decisions or actions (Berman et al., 2018). As a discipline, data science comprises multiple valuable functions that together form a powerful coalition: such functions include (a) code, (b) statistics, and (c) data (Maxwell et al., 2018). The integration of these concepts, when supplemented with scalable computing capabilities, can be an influential tool that provides insights that would otherwise be invisible (Berman et al., 2018). Dakic et al. (2018) explained that data can expose inefficiencies in business processes, which in many situations is made possible by machine learning technologies. Unlike other common business intelligence functions, however, advanced data science concepts such as artificial intelligence and machine learning often direct computers to make decisions on behalf of people, rather than simply play a part in the user's decision-making (Berman et al., 2018; Zhang et al., 2018).

Whereas previous iterations of smarter technologies left computers to follow human-defined logic or use statistical models to aid in human decision-making, artificial intelligence and machine learning technologies in many cases can run autonomously (Zhang et al., 2018). This intentionally has the effect of transferring decision-making abilities to computers (Gauzelina & Bentza, 2017; Pranjic, 2018; Shrestha et al., 2019). Some researchers take a tame approach, stating that data science technologies can provide decision support and that human intuition remains valuable (Kleinberg et al., 2018). Others, however, are more radical, explaining that although intuition is necessary in the present, computers will soon outperform humans by solving the problem of creative leaps (Brennan-Marquez & Henderson, 2019). These advances have led to some researchers, including Zhang et al. (2018), to question if humans should proceed with the development of such technologies. Advanced data science is a powerful tool that can be used to make business decisions faster and in a manner that is rooted in facts, something with which no human can compete (Gauzelina & Bentza, 2017; Pranjic, 2018). The effects of the changing technological landscape are vast; the rapid development of artificial intelligence and machine learning, as well as the resulting effects on countless industries, have been described by Zhang et al. (2018) as a sort of new Industrial Revolution.

Data Maturity Models and Characteristics. Organizations hoping to improve their ability to elicit value from their data must in some way become more mature with respect to business intelligence (Al Rashdi & Nair, 2017; Cech et al., 2018; Chen & Nath, 2018; Farah, 2017; Skyrius et al., 2016). At a high level, Mikalef et al. (2018) defined business analytics maturity as an organization’s ability to transform data into actionable insights. This requires that organizations use all relevant and available resources to get the most out of their collected datasets (Mikalef et al., 2018). The most mature business intelligence solutions are highly complex and supported by management support and technical capabilities (Olszak, 2016). Tavallaei et al. (2015) showed there are a variety of maturity models, most of which comprise various levels evaluated over one or more dimensions.

Researchers frequently provide levels of maturity, typically ranging from immature on-demand data mining through optimal or advanced analysis (Al Rashdi & Nair, 2017; Cech et al., 2018; Farah, 2017; Prieto-Morales et al., 2015). Al Rashdi and Nair (2017) provided the five levels of the Gartner methodology, which include (a) lack of awareness, (b) tactical analysis, (c) focused inquiry, (d) strategic examination, and (e) pervasive analytics. Cech et al. (2018) provided a similar model, giving stages as (a) ad-hoc analysis, (b) defined datasets, (c) integrated systems, (d) optimized evaluation, and (e) advanced business intelligence. Prieto-Morales et al.

(2015) took a somewhat different approach, defining the stages of business intelligence maturity as: (a) not done; (b) defined datasets; (c) practiced analytics; (d) defined datasets and practiced analytics; and (e) defined datasets, practiced analytics, and institutionalized activities. This model makes clear that stages of maturity cannot be achieved independently without first achieving previous goals (Prieto-Morales et al., 2015). Farah (2017) explained that once organizations navigate through the (a) initial stage, they must (b) define their data, (c) manage data and technologies, (d) optimize their decision support systems, and (e) implement recommendations and technology as part of a strategic plan. Farah (2017) also explained that companies must select their desired level of maturity and that organizations should never assume that complete business intelligence maturity is their goal. Organizations must ensure that the benefits obtained through a business intelligence solution outweigh the cost of implementation and the risks associated with avoiding implementation (Farah, 2017).

Many models define maturity in terms of its applications within several dimensions, such as (a) people, (b) processes, and (c) platform (Al Rashdi & Nair, 2017). Lawler and Joseph (2017) more explicitly stated that maturity is a result of (a) business, (b) procedural, and (c) technical factors. This demonstrates that organizations must invest in more than simply the technology behind a business intelligence solution; they must be willing to contribute resources and effort to transforming processes and culture as well (Al Rashdi & Nair, 2017; Lawler & Joseph, 2017). Gannon-Slater et al. (2017) maintained that culture is a required component of big data maturity. Chen and Nath (2018) explained that leaders tasked with growing maturity must focus on (a) their own organization, (b) their organization’s capabilities, (c) the impact they may have, and (d) technology. The researchers show that executive perception of information technology and management support are most correlated to maturity levels and explain that maturity leads to organizational success in key metrics (Chen & Nath, 2018). For organizations to become mature with regard to business intelligence, they must make improvements in each dimension, notably in culture (Al Rashdi & Nair, 2017; Chen & Nath, 2018; Gannon-Slater et al., 2017; Lawler & Joseph, 2017).

When considering the technical side of maturity, organizations must make investments into information technology resources (Chen & Nath, 2018). At the most basic levels of data maturity, investments in this area helps organizations (a) collect, (b) store, and (c) manage their data and begin working with analysts to understand what data are needed and how data will be used at later stages (Salmasi et al., 2016). Knowing the goals of (a) business analysts, (b) statisticians, and (c) data scientists will help data engineers and other information technology professionals know what technical investments must be made to support a business intelligence solution (Salmasi et al., 2016). Boncea et al. (2017) stated that when increasing their technology footprint in business intelligence and especially when purchasing third-party business intelligence software, organizations should search for solutions that contribute to technical maturity. The researchers go on to explain that technical maturity is derived from activities such as (a) documentation, (b) support for multiple platforms, (c) professional certifications, and (d) support programs. Boncea et al. (2017) also stated that organizations often look for capabilities in cloud computing as well. The researchers further show that technology, although not the only aspect of maturity that must be addressed in an organization, is an important dimension that must be considered if businesses hope to reach a desired level of data maturity.

Business must make organizational considerations as well when promoting data maturity (Al Rashdi & Nair, 2017; Lawler & Joseph, 2017; Olszak, 2016; Tavallaei et al., 2015). This is handled primarily by promoting a business intelligence culture or culture of data-driven decision-making (Skyrius et al., 2016). The model proposed by Skyrius et al. (2016) indicated that an organization's culture can be affected by (a) activity between multiple teams, (b) documenting what ideas and processes were or were not successful, (c) creating a sense of community, and (d) management of technology. These dimensions in some form promote the agility and maturity of business intelligence, which in turn leads to the ultimate goal of adoption (Skyrius et al., 2016). Technological advancements supplemented with a strong, robust culture of data-driven decision-making can lead to a winning combination that support data maturity (Chen & Nath, 2018; Farah, 2017; Lawler & Joseph, 2017; Mikalef et al., 2018; Tavallaei et al., 2015).

Summary of Business Intelligence and Data Maturity. Improving decision-making is one of the primary goals of adopting business intelligence technologies at the organizational level (Pappas et al., 2018). Information technology resources are highly important to the implementation of a big data solution, providing the root technology required to collect data and generate meaningful insights and recommendations (Berman et al., 2018; Brynjolfsson & McElheran, 2016; Zhang et al., 2018). Such resources can further be committed to advanced concepts such as artificial intelligence and machine learning to generate even faster results, smarter decisions, and automated action (de Saint Laurent, 2018; Haenlein & Kaplan, 2019; Kaplan & Haenlein, 2019; Shrestha et al., 2019). Information technology resources possess the ability to provide organizations with sound, actionable insights rooted in data, leading to better organizational productivity and profitability (Arghir et al., 2019; Bajari et al., 2019; Nykanen et al., 2016; Popovic et al., 2018). Despite these abilities, organizations must climb the ladder of maturity to achieve the financial results promised by the researchers (Al Rashdi & Nair, 2017; Cech et al., 2018; Farah, 2017; Skyrius et al., 2016; Tavallaei et al., 2015). Data maturity models provide organizations with a roadmap to achieving maturity, beginning with simple ad-hoc analysis and progressing to a fully data-driven enterprise (Cech et al., 2018; Farah, 2017; Skyrius et al., 2016). According to various researchers, organizational culture is the biggest and most frequently forgotten component of data maturity (Bogdan & Lungescu, 2018; Gannon-Slater et al., 2017; Mikalef et al., 2018; Olufemi, 2019).

Culture Transformation

The most common success factor in any business intelligence solution is possession of the proper company culture (Lawler & Joseph, 2017). Company culture has the distinction of having the ability to either encourage or obstruct the execution of organizational strategy (Mehdi et al., 2017). Culture and strategy are inseparable concepts that organizations must consider when making any sort of significant change (Argenti, 2017). Akaegbu and Usoro (2017) explained that culture inspires employees to work in support of or against organizational goals, demonstrating the importance of the compatibility of culture and strategy. Businesses must ensure that their culture is aligned with their strategic goals, encouraging employees to work toward the organization's objectives (Akaegbu & Usoro, 2017; Hassert, 2018; Mehdi et al., 2017; Stacho et al., 2017).

When organizations work toward becoming data-driven enterprise-wide, they must institute a culture that promotes accountability and learning (Gannon-Slater et al., 2017). Culture allows organizations to connect (a) technology, (b) agility, and (c) business intelligence acceptance (Skyrius et al., 2016). A culture of data-driven decision-making consists of various components. Organizations must ensure that their culture encourages (a) fact-based decision-making, (b) appropriate technology skills, and (c) continuous learning (Cekuls, 2015; Garcia-Perez, 2018; Halaweh & El Massry, 2015; Mikalef et al., 2018). Business leaders must publicly and passionately support big data initiatives, as well as provide the appropriate resources that contribute to the success of the project (Grubljesic & Jaklic, 2015; Halaweh & El Massry, 2015; Mesaros et al., 2016; Mikalef et al., 2018; Yeoh & Popovic, 2016). Securing key victories helps foster a sense of trust in data scientists (Cech et al., 2018; Grubljesic & Jaklic, 2015). Finally, organizations should work to embed data-driven decision-making concepts in the organization through (a) processes, (b) repetition, and (c) consistency (Aragona & De Rosa, 2018; Cech et al., 2018; Farrell, 2018; Lawler & Joseph, 2017; Lewis, 2019).

Importance of a Data-Driven Culture. Cech et al. (2018) explained that a data-driven culture is a relatively new concept and that before the 21st century, organizations had little to no access to all streams of data and relied on simpler analysis to make decisions. Data-driven cultures only became important when organizations began to rely on data in decision-making (Cech et al., 2018). Possessing a data-driven culture allows organizations to use data to drive (a) accountability, (b) organizational learning, and (c) other business intelligence initiatives (Gannon-Slater et al., 2017). Skyrius et al. (2016) proposed a model in which organizational culture is the catalyst driving the connection between (a) business intelligence technology, (b) agility, and (c) acceptance, which lead to adoption and actionable insights. A large majority of business intelligence maturity models include culture as a prominent and sometimes leading factor in business intelligence success and maturity (Tavallaei et al., 2015).

Researchers frequently attempt to provide a single formula describing the components necessary to achieve big data success (Mikalef et al., 2018; Tavallaei et al., 2015). At a high level, Mikalef et al. (2018) divided success factors into (a) tangible resources, (b) intangible resources, and (c) human knowledge. Intangible resources, the researchers explain, consist of culture and the alignment between information technology and the remainder of the organization (Mikalef et al., 2018). Halaweh and El Massry (2015) agreed but added that the information technology component of business intelligence is often the simplest to implement. Mesaros et al. (2016) explained that success factors include (a) a prominent project sponsor, (b) cooperation between business units, and (c) a supportive corporate culture. Although overlaps certainly exist between these factors, each can be traced back to the culture underlying organizational operations (Mesaros et al., 2016). Grubljesic and Jaklic (2015) similarly claimed that in addition to the technology and goals of a business intelligence solution, organizations must possess a supportive culture to achieve success. Tavallaei et al. (2015) summarized business intelligence maturity models, highlighting the importance of culture and explaining that nearly every model contains culture either as a dimension of maturity or as a component permeating one or more levels of maturity.

Creating a culture of data-driven decision-making contributes to the success of business intelligence solutions by (a) supporting development and the accuracy of insights, (b) promoting adoption, and (c) facilitating sustainability and long-term usage (Bogdan & Lungescu, 2018; Cech et al., 2018; Halaweh & El Massry, 2015; Mikalef et al., 2018). Cech et al. (2018) explained that when an organization's culture supports business intelligence initiatives, data scientists and business intelligence analysts will be granted access to additional datasets and resources, leading to more accurate results. According to Garcia-Perez (2018), access to organizational resources enables analysts and information technology professionals to better understand the processes that generate data and the dynamics of the data; this understanding reduces the time required to develop big data solutions and improves accuracy of insights. Possessing a supportive culture enables business intelligence professionals to experiment with data and find unique new insights and applications of the data (Lawler & Joseph, 2017). Furthermore, data scientists are afforded the opportunity and resources to create documentation and records of their experiences, an information technology best practice that may be useful at later stages of development (Skyrius et al., 2016). Finally, in always-changing internal and external environments, Villamarin-Garcia and Diaz-Pinzon (2017) explained that possessing a supportive business intelligence culture allows analysts and data scientists to adapt, providing the organization with more accurate and actionable insights.

Garcia-Perez (2018), after stating that culture allows researchers to better understand the processes and dynamics surrounding data, explained that knowledgeable analysts instill trust in the organization. This trust, among other factors, leads to business intelligence adoption and ultimately business intelligence success throughout the organization (Garcia-Perez, 2018). Adoption is a required component of business intelligence success. Bogdan and Lungescu (2018) explained that organizations are unable to take advantage of insights without adoption by key managers and employees. Business intelligence adoption is difficult to achieve, with Halaweh and El Massry (2015) calling the concept a competitive advantage. Supportive cultures lead to change within an organization, transforming employees into analytical, innovative workers who adopt data-driven processes in their decision-making (Halaweh & El Massry, 2015). Skyrius et al. (2016) explained that cultures of data-driven decision-making improve cooperation between departments and builds community, leading to adoption among various different parts of the organization. This valuable component of culture ensures that business intelligence initiatives are not limited to a single group of employees (Skyrius et al., 2016). Yeoh and Popovic (2016) maintained the position that support must come from top-level management and that adoption at this level cascades throughout the organization and leads to widespread adoption enterprise-wide.

Finally, Mikalef et al. (2018) claimed that culture is a useful tool with regard to business intelligence sustainability. The researchers explain that without a properly-implemented culture, business intelligence solutions whither and ultimately fail. However, when cultures are carefully constructed and support smarter analysis, solutions become sustainable and are more likely to succeed (Mikalef et al., 2018). In supporting accuracy, adoption, and sustainability, cultures of data-driven decision-making have a profound impact on the ability of data scientists to achieve their goals (Bogdan & Lungescu, 2018; Cech et al., 2018; Halaweh & El Massry, 2015; Mikalef et al., 2018).

Culture and its Relationship to Strategic Management. In an organizational context, culture can be a valuable supporter or partner of strategic management (Aleong, 2018; Argenti, 2017; Farrell, 2018; Mehdi et al., 2017). According to Mehdi et al. (2017), company culture can either promote or impede the execution of an organization's strategy by manipulating the way employees interpret stimuli in their environment. Researchers generally state that the relationship between culture and strategy in an organization is either causal or, at a minimum, correlated (Argenti, 2017; Mehdi et al., 2017). Argenti (2017) explained that a strong culture influences organizational alignment with its stated strategies. Mehdi et al. (2017) described culture and strategy's relationship as a codependent bond that work together to impact firm performance. Culture is ultimately a core competency of a business that has a tremendous impact on the organization's ability to execute their strategies and cannot readily be copied (Ertem & Kilinc, 2018).

Organizational culture is frequently described as a force that binds organizations together (Aleong, 2018; Farrell, 2018). Aleong (2018) explained that organizations are built on a carefully-cultivated identity, values, and complex processes and procedures and that culture underlies each of these components. Farrell (2018) stated that organizational leaders design strategic initiatives but that organizational culture must support the behaviors that lead to a successful implementation of the chosen strategy. The right culture, Aleong (2018) explained, is a necessity when applying a strategy to an organization. Strategic managers must use culture to set the vision driving their plans and initiatives (Farrell, 2018).

The implementation of a business intelligence solution is indicative of an organization's desire to become data-driven with regard to its decision-making (Bogdan & Lungescu, 2018). Ylijoki and Porras (2016) noted that decision-making cannot become consistently data-driven, however, without possessing the appropriate culture. The appropriate culture, the researcher's state, influences the strategic management of the organization (Ylijoki & Porras, 2016). Culture facilitates the execution of a particular strategy, although an unsupportive environment can be detrimental to the goals of strategic managers (Calof et al., 2017). In the context of business intelligence, Calof et al. (2017) explained that company culture must promote quick decision-making so that organizations avoid becoming paralyzed by data or ignoring data altogether. Culture must also encourage decision-makers at all levels to become educated in business intelligence concepts so that employees can work to implement the strategic plans of the organization without stumbling over common misconceptions (Kimble & Milolidakis, 2015). Leaders and business users must support changes in culture for such changes to be realized (Thamir & Poulis, 2015).

Researchers frequently discuss the components necessary to transform a culture to support strategic decisions (Ahmadi et al., 2016; Bogdan & Lungescu, 2018; Foster et al., 2015; Morton et al., 2018). Business must organize resources in such a way that supports their strategic designs and receive support from the highest levels of the firm (Bogdan & Lungescu, 2018).

Ahmadi et al. (2016) took a grim approach, explaining that organizations in the United States are in need of decision-makers that understand business intelligence concepts. Business leaders may instruct employees to explore new technologies through iterations and experiments, leading to a reinforced culture of strategic management (Morton et al., 2018). Creating the right culture supports strategic decision-making, although such a change can be time-consuming (Foster et al., 2015).

Culture as a Catalyst for Execution of Strategy. In an organizational context, researchers often find that company culture serves as a catalyst for the implementation of a strategic plan (Akaegbu & Usoro, 2017; Hassert, 2018; Mehdi et al., 2017). Akaegbu and Usoro (2017) explained that the right corporate culture will encourage employees to work toward their chosen strategy. Mehdi et al. (2017) added that although culture can propel implementation forward, the wrong culture can be a hindrance to execution. Because human employees are fundamentally independent and uncontrollable, strategies that require their involvement must be backed by a culture that influences them to perform the necessary work (Mehdi et al., 2017). Execution methodologies should be planned with organizational culture in mind so that culture can be used to promote implementation (Hassert, 2018).

For organizations to capitalize on culture’s ability to catalyze the execution of strategy, they must ensure that their culture is compatible with the strategy itself (Hassert, 2018; Mehdi et al., 2017). Hassert (2018) explained that the design and execution of strategy are often disconnected but that an effective, well-matched culture can protect the organization’s ability to move forward with their plans. Akaegbu and Usoro (2017) provided five qualities of culture that influence strategic execution, including (a) strong leadership, (b) adaptability, (c) creativity, (d) collaboration and teamwork, and (e) innovation. El Khouly et al. (2017) further explained that leaders must employ proper leadership styles to positively affect the implementation of strategic plans. The researchers show that forms of leadership such as the (a) autocratic, (b) laissez-faire, and (c) participative styles can impact an organization's ability to implement strategy, though democratic forms of leadership do not (El Khouly et al., 2017). Ultimately, unless organizations are completely autocratic, companies must address their culture to ensure that it is aligned with their chosen strategies (Mehdi et al., 2017). A rich culture in alignment with an organization's strategies will catalyze their implementation and propel the organization toward its strategic plans (Mehdi et al., 2017).

Transformation of Culture. Organizations look to transform their corporate culture so that they may maximize human potential and facilitate organizational change (Dimitrova, 2018). The proper culture in an organization will bind employees more closely to their work and significantly affect their work ethic and activity (Stacho et al., 2017). According to Dimitrova (2018), culture consists of the unseen foundation that runs in parallel with observable actions and processes within an organization. The principles upon which a business is built include their (a) company values, (b) standards, and (c) accepted conventions and traditions (Dimitrova, 2018). Organizations must find ways to align their culture with their strategic goals so that employees can become more closely attached to the goals of the company (Akaegbu & Usoro, 2017; Hassert, 2018; Mehdi et al., 2017; Stacho et al., 2017).

Generally speaking, organizations must work to implement or at least maintain and protect their chosen culture; doing so will ensure that they understand their own principles and ensure that strategies are mutually supportive of culture (Argenti, 2017; Farrell, 2018; Knapp, 2016; Lewis, 2019; Stacho et al., 2017). Stacho et al. (2017) maintained that businesses should work to create an environment in which employee behavior is steered in a direction that supports the strategies and goals of the organization. The first step in creating and maintaining this environment, Farrell (2018) stated, is by understanding the existing culture and the gaps that lie between current and desired culture. Leaders can use a variety of tools, including surveys or interviews, to understand the current state and to determine if employees in the business are receptive to change (Farrell, 2018). Argenti (2017) explained that in an organization hoping to radically transform or even slightly modify their culture, leaders absolutely must be present. Absent leaders will be unable to instill culture in employees, who frequently look to leadership for guidance (Argenti, 2017). In this vein, Farrell (2018) suggested that leaders lead by example, invoking the adage that actions speak louder than words. Because employees respond well to reinforcement through patterns, business leaders and change agents must provide consistency in behavior (Farrell, 2018). Using ideas similar to the behavioral psychology theories of Ivan Pavlov and B. F. Skinner, Farrell (2018) suggested that organizations should reward employees' adherence to cultural behaviors and punish deviance from these principles.

Lewis (2019) explained that culture promotion should occur in five distinct dimensions, including (a) diversity, (b) employee morale, (c) professional development and learning, (d) new employee onboarding, and (e) organizational communication. He goes on to show that organizations that hope to make strides with a new or enhanced culture must focus on each of these five dimensions to find success. Businesses may institute initiatives such as (a) workshops and retreats, (b) regular climate checks, and (c) team boards to monitor and implement cultural principles across each of the five dimensions (Lewis, 2019). Knapp (2016) explained that teamwork and building up others is a winning formula to create engaged employees. In this way, employees can take ownership of their work and improve results (Knapp, 2016). Farrell (2018) stated that employees on-board with and in-compliance with an organization's culture will support new strategic initiatives, especially if they are a stakeholder in new projects.

Although the principles governing a culture transformation are generally universal, instituting a culture of data-driven decision-making has unique aspects that should be addressed by organizations (Ahmadi et al., 2016; Calof et al., 2017; Foster et al., 2015). Most importantly, researchers explain that business intelligence initiatives should have support at the highest levels of the organization (Calof et al., 2017; Foster et al., 2015). Calof et al. (2017) explained that data-driven cultures should be sponsored at the executive level. Foster et al. (2015) describe top-down support as a best practice for business intelligence. Calof et al. (2017) elaborated, showing that shallow, horizontal organizational structures are most successful in transforming into a data-driven culture. Foster et al. (2015) agreed, showing that organizations that avoid redundancy and duplication of efforts often find the most success. Ahmadi et al. (2016) explained that although executive sponsors and top-down support is critical, leaders must also ensure that policies and procedures within their organizations support a culture of data-driven decision-making. Furthermore, the researchers state that for businesses to most accurately take advantage of data-driven enhancements, leaders and employees at all levels of the organization must be educated in the basic principles and applications of business intelligence. The modern workforce, Ahmadi et al. (2016) stated, is in desperate need of individuals who understand the outputs and applications of business intelligence solutions. Kimble and Milolidakis (2015) found that employees and even executive leaders commonly believe misconceptions surrounding business intelligence. The responsibility for education lies with leaders who should work to provide training and instructional resources to employees with the ultimate goal of teaching employees how to consume and process information themselves (Foster et al., 2015).

Organizational procedures must be supportive of and consistent with a culture of data-driven decision-making (Ahmadi et al., 2016). This includes obtaining the proper structure within information technology as well as structures, both organizational and cultural, throughout the remainder of the business (Ahmadi et al., 2016). Within information technology, Foster et al. (2015) explained that standards and best practices should be codified so that employees follow consistent procedures and protect the validity of data and analyses. In more operational and strategic positions throughout the organizations, metrics should be implemented that describe adherence to big data solutions and measure the success of business intelligence applications (Foster et al., 2015). Because culture must be the primary driver of employee desire to adopt business intelligence initiatives, policies must be applied that align with such a culture (Ahmadi et al., 2016; Foster et al., 2015).

In the initial stages of a culture transformation, change agents must seize upon momentum and take advantage of opportunities quickly (Calof et al., 2017; Foster et al., 2015). Calof et al. (2017) explained that leaders must make fast decisions and demonstrate the use of business intelligence across the organization. Foster et al. (2015) suggested that business intelligence teams find opportunities for quick victories so that organizations continue to invest financial and non-financial resources. The researchers show that these early triumphs help, from an internal marketing perspective, to convince skeptics to consider the possibilities associated with business intelligence. Finally, business intelligence teams should work to improve their soft skills so that they may more positively and effectively communicate with end users and win their trust (Foster et al., 2015).

Maximizing the potential of employees requires organizations to instill a culture that is in alignment with strategic plans (Akaegbu & Usoro, 2017; Dimitrova, 2018; Hassert, 2018; Mehdi et al., 2017; Stacho et al., 2017). Leaders should take stock of the existing culture and find ways to move toward an environment that supports organizational goals (Farrell, 2018; Stacho et al., 2017). Promoting a culture must occur across various areas of an organization and be consistently and repetitively applied over a long period of time (Farrell, 2018; Lewis, 2019). Organizations hoping to implement a culture of data-driven decision-making should follow the best practices outlined by Foster et al. (2015) and corroborated by researchers such as Ahmadi et al. (2016) and Calof et al. (2017). Following such practices should provide organizations with the best chances of successfully implementing a business intelligence culture (Ahmadi et al., 2016; Farrell, 2018; Mehdi et al., 2017).

History and Future of Cultures of Data-Driven Decision-Making. Cultures of intelligent decision-making based on facts and data can be traced at least as far back as China in the 3000s BC and, more recently, in texts such as Sun Tzu's *Art of War* (Prinsloo, 2016). Modern business intelligence initiatives originated in the 1940s in response to the Second World War (Haenlein & Kaplan, 2019). The rapid evolution of technology has led to significant advancements in data-driven decision-making over the remainder of the 20th century and the beginning of the 21st (Grable & Lyons, 2018; Haenlein & Kaplan, 2019). Barua and Mondal (2019) and Wixom et al. (2014) explained that the technological difficulties of implementing big data solutions from the ground up has led to some organizations electing to forego business intelligence altogether, at least when implemented through internal resources. Despite some setbacks, Surijah (2016) and Ozer (2015) explained that change in the external environment is accelerating and organizations must turn to business intelligence to maintain pace with their competition.

Although organizational culture has always been an important consideration for businesses, it has become mandatory for companies looking to impact performance through data-driven decision-making (Chen et al., 2012). Modern businesses, however, are frequently unable to implement a culture that is in alignment with their strategic goals, leading to diminished financial results (Bogdan & Lungescu, 2018; Galbraith, 2014; Grover et al., 2018; Olufemi, 2019). Bogdan and Lungescu (2018) and Galbraith (2014) stated that even organizations that possess the technical skills to implement business intelligence have problems implementing a sufficient culture. Organizations may desire to adopt a culture of data-driven decision-making but are often unequipped to transform their culture (Olufemi, 2019). Frequently, business managers resist cultural change because they perceive business intelligence as a challenge to their authority and decision-making abilities (Bogdan & Lungescu, 2018; Galbraith, 2014). This leads to a lack of support of data scientists, which causes a significant breakdown in business intelligence endeavors (Grover et al., 2018).

The future of business intelligence is bright; although some organizations opt to turn away from the advantages it offers (Barua & Mondal, 2019; Wixom et al., 2014), technology and its delivery formats are being developed and introduced rapidly (Grable & Lyons, 2018; Haenlein & Kaplan, 2019). Chattopadhyay (2016) suggested that businesses should move away from the typical dashboard reporting and to even newer forms of analysis using big data. Organizations and the business intelligence community at-large must strive to find ways to implement cultures of intelligent systems to allow the industry to continue growing and dominating (Gauzelina & Bentza, 2017; Ward et al., 2019). In doing so, these groups will encourage organizations to adopt decision-making processes and automated procedures based on evidence gathered through data (Garcia-Perez, 2018; Halaweh & El Massry, 2015).

Characteristics of a Culture of Data-Driven Decision-Making. Businesses aiming to transform their culture into one of data-driven decision-making should understand their current culture and aspects of the culture they desire (Cech et al., 2018; Mudzana & Maharaj, 2017; Skyrius et al., 2016; Villamarin-Garcia & Diaz-Pinzon, 2017). Organizations should first spend time evaluating their existing decision-making processes and whether such processes address the problems facing the business (Cech et al., 2018). Villamarin-Garcia and Diaz-Pinzon (2017) stated that to successfully implement a business intelligence solution, leaders must evaluate their current environment and ensure that conditions are favorable throughout the (a) planning, (b) development, and (c) execution processes. The environment, according to the researchers, must include organizational culture and has the potential to create roadblocks or catalyze change (Villamarin-Garcia & Diaz-Pinzon, 2017). Mudzana and Maharaj (2017) explained that organizations should understand the needs of their users and tailor any implementation strategy to their unique needs and demands. Ultimately, Skyrius et al. (2016) showed that any business intelligence implementation is ultimately driven by a proper organizational culture.

Many researchers find that organizations should work to implement a fact-based culture and develop a staff skilled in information technology and capable of speaking to executive leadership and end users (Garcia-Perez, 2018; Halaweh & El Massry, 2015; Mikalef et al., 2018). Businesses must allow facts to drive operational decision-making so that they can positively affect metrics at the organizational level (Mikalef et al., 2018). An important component of a fact-based culture is instilling trust throughout the organization (Garcia-Perez, 2018). Consequently, data scientists and other business intelligence professionals must have a thorough knowledge of the processes and qualities of data so that they can better speak to its uses and meanings (Garcia-Perez, 2018). Grubljesic and Jaklic (2015) explained that this also allows data scientists and researchers to manage expectations throughout the organization. According to Halaweh and El Massry (2015), these capabilities require practitioners to possess an analytical mindset and innovative drive. Finally, Cekuls (2015) explained that organizational culture should promote knowledge and learning among both data scientists and business users so that all members of the business can read and interpret data outputs.

One of the most important aspects of a culture of data-driven decision-making involves obtaining buy-in from key individuals and the business intelligence team itself (Grubljesic & Jaklic, 2015; Halaweh & El Massry, 2015; Mesaros et al., 2016; Mikalef et al., 2018; Yeoh & Popovic, 2016). Executive sponsors can signal their support for a big data initiative by formalizing a team tasked with implementing business intelligence solutions (Yeoh & Popovic, 2016). Organizations are best served by a business intelligence staff consisting of a project champion, external experienced consultant, and a mixture of business and internal technical resources (Yeoh & Popovic, 2016). Mikalef et al. (2018) elaborated that leaders must also prioritize investments in business intelligence technologies and demonstrate successful usage of new decision-making tools. Grubljesic and Jaklic (2015) concurred, explaining that an executive sponsor must be supportive both publicly and prominently. Mesaros et al. (2016) asserted that a strong executive champion enables initiatives to permeate throughout the entire organization. Support from top management is an essential part of culture transformation and could be considered a competitive advantage (Halaweh & El Massry, 2015).

Yeoh and Popovic (2016) further explained that commitment to business intelligence initiatives must come from the business intelligence team as well. Confident, capable data scientists and engineers will instill trust in business users throughout the organization (Yeoh & Popovic, 2016). Mesaros et al. (2016) explained that the right team must be assembled and must work in cooperation with one another. Grubljesic and Jaklic (2015) urged practitioners to include end users in the development of business intelligence tools. According to Skyrius et al. (2016), business intelligence teams can earn trust by becoming truly cross-functional and including employees from all areas of the organization and fostering a sense of community. Such actions encourage organizational support for business intelligence initiatives even before they are formally launched for widespread consumption (Grubljesic & Jaklic, 2015; Mesaros et al., 2016; Skyrius et al., 2016; Yeoh & Popovic, 2016).

In modern organizations, business intelligence projects must return results quickly to avoid losing momentum (Cech et al., 2018; Grubljesic & Jaklic, 2015). Researchers indicate that simple projects with high rates of return are a useful way to gain confidence in the power of data analysis (Grubljesic & Jaklic, 2015). Cech et al. (2018) explained that such projects should be attempted early in the development process to ensure that users and executives are recruited as early supporters. These early victories support a culture of data-driven decision-making and are necessary for the long-term success of the initiative (Cech et al., 2018).

Organizations should strive to embed data-driven decision-making processes in the culture of the business and ingrain these principles in their employees (Aragona & De Rosa, 2018; Cech et al., 2018; Lawler & Joseph, 2017). Aragona and De Rosa (2018) explained that (a) technology, (b) devices, and (c) processes should be connected to (a) organizational values, (b) symbols and logos, and (c) policies. These actions force business intelligence practices to become embedded in organizational processes by contributing to the characterization of culture (Aragona & De Rosa, 2018). Lawler and Joseph (2017) explained that organizations must become mature by improving processes and technical factors and that processes should be codified into the fabric of the business. Such practices must be implemented across the entirety of the organization (Mesaros et al., 2016). Consistent with the suggestions of Farrell (2018) and Lewis (2019), embedding data-driven decision-making in an organization's culture requires consistency and repetition. Using these principles, organizations should become slightly more mature with every action (Cech et al., 2018). Slowly building maturity one step at a time ensures that organizations most effectively implement a long-lasting culture of data-driven decision-making (Cech et al., 2018).

Summary of Culture Transformation. Culture and organizational strategy are inseparably linked (Argenti, 2017). Ensuring that culture and strategic plans are in alignment with one another is one of the most prominent success factors in new strategy development (Akaegbu & Usoro, 2017; Mehdi et al., 2017). Transforming a company culture requires significant investment in consistent and repetitive actions (Farrell, 2018; Lewis, 2019). Such transformation is radical but ultimately necessary to maximize the chances of success in a business intelligence initiative (Lawler & Joseph, 2017). Organizations looking to become data-driven with regard to their decision-making should (a) promote fact-based decision-making, (b) secure strong, dedicated executive sponsors, (c) achieve early victories, and (d) institutionalize supportive procedures throughout their business (Aragona & De Rosa, 2018; Cech et al., 2018; Garcia-Perez, 2018; Grubljesic & Jaklic, 2015; Halaweh & El Massry, 2015; Lawler & Joseph, 2017; Mesaros et al., 2016; Mikalef et al., 2018; Yeoh & Popovic, 2016).

Potential Themes and Perceptions

This research study was performed at USA Truck, Inc., a publicly-traded full truckload carrier and freight brokerage organization located in Van Buren, Arkansas. The company's asset operations occurred chiefly in the southeast and eastern regions of the United States while the non-asset and asset-light divisions served the entire United States and Mexico. The organization began as a division of Arkansas Best Freight in Fort Smith, Arkansas before being purchased by Robert Powell, Breck Speed, and Jerry Orler in 1983. The original fleet size began at 10 units in operation and grew to nearly 2000 units by 2003. The following decade saw the organization expand into various new operations. Buoyed by the over-the-road irregular route trucking business, USA Truck developed to include (a) logistics and intermodal services, (b) dedicated routes, (c) power-plus fleets, (d) flatbed deliveries, and (e) limited less-than-truckload ventures.

The organization reported financials quarterly in three segments, consisting of (a) trucking, (b) logistics, and (c) Davis Transfer, a 2018 acquisition. The trucking business included irregular and dedicated lanes in the southeast and eastern United States, with some business moving across the southern border into Mexico. This business was supported by (a) driver dispatchers, (b) freight coordinators, (c) customer service personnel, (d) trainers, and (e) maintenance personnel. Employees supporting this division were located primarily in Arkansas, with trainers and maintenance personnel scattered throughout (a) Arkansas, (b) Texas, (c) Ohio, and (d) Georgia. The logistics division included a variety of freight brokerage offices headquartered in Arkansas but with offices scattered throughout all regions of the United States. The organization maintained sales offices throughout the United States as well. The remaining non-driving employees, including (a) information technology, (b) human resource, and (c) financial personnel, resided primarily in Arkansas and were tasked with supporting the entire organization.

Because this study focused on the strategic ways organizations can implement cultures of data-driven decision-making, groups selected to target include (a) information technology, (b) financial reporting, (c) operational leadership, and (d) executive leadership. Each of these departments was relevant in creating the appropriate culture (Grubljesic & Jaklic, 2015; Mesaros et al., 2016; Skyrius et al., 2016). The organization maintained a cross-functional strategic reporting and data science team consisting of personnel representing the information technology and financial reporting groups, following the guidance of Halaweh and El Massry (2015) and Skyrius et al. (2016). USA Truck invested in enhancing their technological capabilities by hiring full-time application developers and data engineers and accelerated these efforts by utilizing contractors based in Texas and South Africa, a move championed by Mesaros et al. (2016). This team was responsible for providing data-driven solutions to the organization, including reporting and algorithm-based automation.

USA Truck worked diligently to improve their data maturity, consistent with the suggestions of Cech et al. (2018) and Farah (2017). This transformation began in 2017 with the construction of an enterprise data warehouse, followed by enhanced reporting capabilities in 2018 and concrete steps into the artificial intelligence space in 2020. Concurrent with these technical achievements was the transformation of culture into one that supports data-driven decision-making. The organization unwittingly was following the guidance of Farrell (2018) and Lewis (2019), consistently and repetitively applying data-driven principles throughout the business. The extended implementation period endured by the organization allowed the business to build a strong infrastructure supporting an embedded culture of data-driven decision-making (Cech et al., 2018). Immediate future steps included (a) improving technological security and capability by transitioning to a cloud-based environment, (b) expanding investments in data science by hiring additional resources, and (c) systematically replacing flawed human systems with reliable, data-driven approaches where appropriate.

Summary of the Literature Review

The review of the literature demonstrates three significant aspects of cultures of data-driven decision-making that researchers and practitioners should remember. Being aware of decision models and the ways human decision-makers logically arrive at a choice helps understand how quantitative data analysis and insights can influence the quality of those choices (Cao, 2017). Leaders should understand how technology can affect their organization and should guide their businesses to more advanced forms of data maturity, using models proposed by researchers (Al Rashdi & Nair, 2017; Cech et al., 2018; Farah, 2017; Skyrius et al., 2016; Tavallaei et al., 2015). Business leaders should be aware that although technology is important in a business intelligence solution, the most significant success factor comes in the form of organizational culture (Garcia-Perez, 2018; Halaweh & El Massry, 2015). Corporate cultures must be aligned with strategic directions so that organizations are best equipped for success (Akaegbu & Usoro, 2017; Argenti, 2017). Leaders must understand the concepts underlying cultures of data-driven decision-making and pursue them consistently and repetitively (Farrell, 2018; Gannon-Slater et al., 2017; Lewis, 2019). Although research surrounding cultures of data-driven decision-making has identified many significant aspects of the topic, further research is needed with regard to the specific ways small to medium-sized organizations can transform their company culture.

Transition and Summary of Section 1

Section 1 identifies a significant problem found in organizations in that companies frequently fail to implement data-driven cultures. This section also provides a description of the concepts regarding data-driven decision-making and an accompanying supportive culture. A justification is given for the qualitative case study research methodology and design. A review of the current literature identifies the major topics of interest to contemporary researchers and includes (a) decision-making, (b) applications of technology and associated data maturity, and (c) culture transformation and data-driven cultures. A deeper look at the current literature reveals trends that will be of particular interest as the study progresses and ensures that there is a need for studying cultures of data-driven decision-making.

Section 2: The Project

Strategic decision-making, an integral function of business management, can be strongly aided by capabilities in the field of information technology (Brynjolfsson & McElheran, 2016; Jabeen et al., 2016; Morton et al., 2018). Organizations can count data as one of their most important assets and the ability to act on insights as one of their competitive advantages (Ylijoki & Porras, 2016). Garcia-Perez (2018) and Halaweh and El Massry (2015) suggested that the appropriate business culture is required before organizations can take advantage of the rewards afforded by big data consumption and analysis. Despite the possession of data and even technical capabilities regarding its analysis and integration, many organizations are unable to execute due to their lack of an appropriate culture (Bogdan & Lungescu, 2018; Olufemi, 2019). Alameen et al. (2016) and Roth (2016) claimed the transportation industry has an unusually weak relationship with cultures of data-driven decision-making. The objective of this project was to research how businesses transform their culture into one that supports data-driven decision-making. The second section of this study focuses on defining the parameters of the research in such a way that readers can understand and replicate the inquiry. This section opens with a purpose statement and defines (a) the role of the researcher, (b) participants, (c) research methodology and design, (d) populations and sampling, and (e) how the researcher collected and organized data. This section also addresses the ways in which the study approached reliability and validity of the results.

Purpose Statement

The purpose of this qualitative case study was to add to the existing body of knowledge and improve the understanding of a data-driven culture transformation by analyzing the ways in which organizations implement data-driven strategies. Researchers claim that if such processes can be understood and replicated, organizations can create data models and implement new technologies that can support productivity and improve performance (Garcia-Perez, 2018; Halaweh & El Massry, 2015). For the purpose of this study, a qualitative methodology was utilized. Because the intent was to understand the essence of the experience, flexible qualitative methodologies were preferred (Guillen, 2019).

A case study was used, limiting the participants to a single organization; considerations were made to ensure that results are transferable to other organizations of similar size, consistent with the assertions of Lincoln and Guba (1985). In particular, Lincoln and Guba's (1985) concept of thick description was used to establish the context surrounding interviews. This ensured that readers can understand the insights gained from data and determine whether these conclusions are transferable. The study was intended to explore the processes by which an organization fosters a culture of accountability and productivity. The research worked to understand how a business can replace faulty, human-centric decision processes with more reliable and consistent technological and mathematics-based algorithms. The focus of the study was on a single organization working to instill a data-driven environment. The organization's goals of creating a data-driven culture, as well as to replace decision-making power with smarter processes, were in alignment with the stated goals and research questions of interest in this study. The generalized problem was investigated through a detailed review of employee experiences at USA Truck, a publicly traded Arkansas-based transportation and logistics organization.

Role of the Researcher

According to Roger et al. (2018), the researcher in a qualitative study is responsible for conducting research by searching for the essence of an experience. The writers explain that it is the researcher's job to (a) look for, (b) transcribe, (c) understand, and (d) analyze participants' narratives and that the researcher is ultimately the steward of these accounts (Roger et al., 2018). The researcher in this study adopted a worldview supportive of qualitative research. According to Bettoni (2018), Kalu (2019), and Kim and Donaldson (2018), this required a subjective interpretation of the world within a constructivist worldview. The researcher relied on observable, not measurable, phenomena to appropriately construct and defend theories (O'Connor et al., 2018). Annansingh and Howell (2016) suggested that case studies are a useful methodology for researchers performing constructivist or qualitative forms of research. The all-encompassing role of the researcher in a qualitative study is to give participants a platform to explain the nature of a phenomenon, then interpret these findings (Belotto, 2018; Guillen, 2019).

The researcher was first responsible for identifying and gaining access to participants. Clark and Veale (2018) explained that the researcher must be given access to participants' regular setting and adopt a participatory role in the study. This improves the quality of the data and to a degree works to protect participants from potential harm (Clark & Veale, 2018). Ngozwana (2018) stated that the researcher must define the population of interest within the study and, if necessary, narrow participants to a smaller, manageable sample. The researcher selected an appropriate sampling methodology and determine the format of sessions with participants (Ngozwana, 2018).

In the qualitative study, the researcher was next responsible for gathering data that helps form a theory regarding a phenomenon (Creswell & Creswell, 2018; Creswell & Poth, 2018; Yin, 2018). Denzin and Lincoln (1998) asserted that qualitative research allows more flexibility within a study's methodology and the researcher's objectivity. However, researchers must still work to reduce bias and ensure that any potential biases are well-documented (Clark & Veale, 2018). Thurairajah (2019) explained that researchers must decide what boundaries to erect when working with participants. Researchers may be comfortable sharing their personality with participants to build rapport, though they must be careful to address any potential bias this introduces with regard to participant input (Thurairajah, 2019). Although the researcher aimed to collect information that helped form theories with respect to the area of interest, the researcher's primary goal throughout this process was the safety of participants (Ngozwana, 2018; Surmiak, 2018; Thurairajah, 2019). This hearkened to Thurairajah's (2019) assertion that boundaries are necessary within a qualitative study. Due to the often-sensitive nature of topics within qualitative research topics, the researcher was responsible for protecting participants by maintaining their anonymity and confidentiality (Ngozwana, 2018; Surmiak, 2018).

After collecting participant feedback and collecting any documents or other useful articles to consider, the researcher analyzed data and reported findings. The researcher transcribed interviews and processed information through coding, an act that involved tagging useful and recurring information throughout different participant interactions (Belotto, 2018; Clark & Veale, 2018). Rose and Lennerholt (2017) proposed a revolutionary way of performing this process, explaining that researchers can use complex text mining algorithms to analyze and sort documents and interview transcripts for recurring themes. Once the researcher identified and connected key themes, the researcher engaged in reflective and interpretive thinking (Clark & Veale, 2018). This allowed the researcher to identify and control for possible biases, as well as ensure that insights gathered are accurately derived from data and participant input (Clark & Veale, 2018).

The researcher was lastly responsible for presenting findings in such a way that evoked reliability. Lincoln and Guba (1985) suggested achieving trustworthiness in an academic study by reassuring the audience that findings are (a) credible, (b) transferable, (c) dependable, and (d) confirmable. These aspects of a researcher's responsibility to a study were required to safely obtain results acceptable by the academic community. The role of the researcher in this study involved (a) adopting an appropriate worldview, (b) gaining access and developing rapport with participants, (c) ensuring participant safety and confidentiality, (d) collecting and analyzing data, and (e) presenting findings.

In this study, the researcher was responsible for all data collection and analysis, which comprised tasks such as conducting interviews and coding data but also expanded to include administrative tasks (Belotto, 2018; Clark & Veale, 2018; Creswell & Creswell, 2018; Creswell & Poth, 2018). The researcher was responsible for obtaining all institutional approvals to proceed with the study, including from departmental leaders and the institutional review board. As a next step, the researcher was then responsible for gaining access to the participants by receiving written approval from organizational leaders (Clark & Veale, 2018). Appendix B includes a signed permission letter. Once this was complete, participants were selected using purposive sampling methods and formally invited to join the study (Ngozwana, 2018). A sample recruitment letter is provided in Appendix C. Participants were provided with all appropriate disclosures and consent forms, as shown in Appendix D. The researcher then (a) interviewed all willing participants in their environment, (b) gathered all accompanying sources of data, and (c) coded and analyzed these results. Finally, the researcher was ultimately responsible for drawing relevant conclusions and ensuring reliability and credibility of the study's results.

Participants

In a qualitative study, participants must be found that generate the body of evidence that forms the basis for all conclusions drawn from the research (Creswell & Creswell, 2018; Creswell & Poth, 2018). Gentles et al. (2015) suggested that the participant in a case study refers first to the study's *case*, then attributes of the case that can provide related information. The researchers explain that in this sense, an organization is made up of many individuals, many of whom may be eligible to serve as a resource from which to elicit information about the case. Individuals, the researchers explain, should be selected based on the likelihood they can provide useful and relevant information about the organization (or case) related to the topics of interest (Gentles et al., 2015). Frequently, participants in case studies are selected using the snowball or related method, which suggests finding a small group of dedicated, influential participants who recruit additional participants throughout the organization (Marcus et al., 2017). However, this method has been shown to introduce a degree of bias or even fabricated results, particularly when a participant has poor relationships within the organization, endures restrictions, or sees the organization negatively (Marcus et al., 2017). Geddes et al. (2018) instead recommended avoiding this methodology and recruiting a wider set of participants. Using a horizontal network rather than vertical, Geddes et al. (2018) argued that researchers can avoid issues that arise when other methods fail to gain traction in an organization.

Peticca-Harris et al. (2016) suggested that studies cannot move forward without gaining access to the environment of interest. This involves (a) identifying, (b) contacting, and (c) interacting with participants, tasks that inherently require a high level of access to an organization (Peticca-Harris et al., 2016). Riese (2019) explained that access in the context of a qualitative study refers to a researcher's ability to gain admittance to an environment. This access affects dimensions considered by the researcher as well as the extent to which the researcher must protect him or herself and participants (Riese, 2019). Shenton and Hayter (2004) offered several ways to gain access to participants and build trust, including making personal improvements such as (a) offering honest answers to employees, (b) becoming receptive to new ideas, and (c) showing a strong background with significant experience in the relevant field. Furthermore, researchers can be aided by organizational leaders by receiving their endorsements or being introduced slowly to an organization over time (Shenton & Hayter, 2004). Researchers must improve their ability to connect with organizations and their employees so that trust can be earned quickly from potential participants in the company (Riese, 2019).

Building relationships with participants in a qualitative study continues well past the initial gaining of access to their environment. Kalman (2019) suggested that maintaining rapport with research participants is a difficult task. Researchers frequently conduct interviews and, due to a lack of a developed relationship and high participant anxiety, are unable to elicit useful information from participants (Kalman, 2019). O’Grady (2016) explained that when interviewers and researchers develop relationships with participants, they build trust and the quality of participant contributions increases. Better rapport strongly indicates that participants are more willing to disclose information and improves the accuracy and truthfulness of their responses (O’Grady, 2016). Rapport is a precursor to social closeness and leads to richer descriptions of a phenomenon (Weller, 2007).

It is important for researchers to establish and continuously re-establish rapport with participants (Weller, 2017). Alase (2017) suggested that researchers can establish these relationships by keeping interviews participant-oriented through an interpretative phenomenological approach. Such an approach reiterates the primary goal of qualitative research—to understand the essence of an experience—by encouraging participants to provide information in their own words without causing distortion of their experiences (Alase, 2017). Generally speaking, two individuals can build rapport through (a) laughing together, (b) appreciating one another, (c) connecting, (d) discussing interesting topics, and (e) avoiding deviance from the task or topic of interest (Turaga, 2019). In the 21st century, interviewers must grapple with challenges introduced by technology and distance interviews (Weller, 2017). In all interactions with participants, researchers should remember to integrate themselves with participants' environments and establish genuine relationships; doing so leads to more and better data (Alase, 2017; O'Grady, 2016; Weller, 2017).

When working with participants and when analyzing and reporting on the collected data, researchers must ensure that participants are protected from any potential harm (Creswell & Creswell, 2018; Creswell & Poth, 2018; Yin, 2018). Creswell and Poth (2018) summarized ethical considerations as a concern for the general welfare of participants in the study. In a qualitative environment, researchers should protect their participants by (a) obtaining written informed consent, (b) anticipating and protecting against harm and deception from all sources, (c) protecting against breaches of privacy or confidentiality, (d) providing special protections for vulnerable groups, and (e) recruiting participants with different perspectives to ensure that all affected groups are represented (Yin, 2018). Researchers should document their processes and actions regarding ethical issues to create proof of compliance with ethical standards (Creswell & Creswell, 2018; Creswell & Poth, 2018). Despite the presence of review boards and the passage of laws mandating ethical treatment of individuals, Stake (2010) argued that researchers should hold themselves to a higher standard. Review boards and governing bodies are often separated from the actual research being performed and are sometimes unable to effectively monitor interactions with participants; therefore, the most effective monitor of ethical considerations is often the researchers themselves (Stake, 2010). As explained by Ngozwana (2018), Surmiak (2018), and Thurairajah (2019), researchers must unapologetically support participant safety. For this study, all five recommendations provided by Yin (2018) were closely followed. The researcher worked to obtain informed consent from all participants (Appendix D) and followed standard procedures for (a) maintaining confidentiality, (b) protecting against harm, and (c) protecting any potentially vulnerable participants. All procedures were supported by appropriate documentation. Furthermore, participants were recruited from a variety of backgrounds, ensuring equitable participation as supported by Yin (2018).

Utilizing the theories presented, the researcher in this study took steps to properly and safely (a) identify, (b) recruit, and (c) interview participants (Creswell & Creswell, 2018; Creswell & Poth, 2018; Yin, 2018). The researcher gained permission to contact participants from the institutional review board as well as leaders of the organization selected for the case study (Clark & Veale, 2018; Riese, 2019; Yin, 2018). A signed permission letter authorizing the researcher to conduct on-site interviews is provided in Appendix B. Participants were identified through purposive sampling methods to seek the most useful and rich descriptions of the phenomena of interest (Ngozwana, 2018). The researcher identified 20 individuals from diverse backgrounds within the organization and invited to join the study using a recruitment letter (Appendix C). Had 20 individuals not been identified, snowball methods would have been used to recruit additional participants (Marcus et al., 2017). The researcher provided disclosures to participants and obtained written consent before conducting interviews, using the consent document provided in Appendix D. Measures were taken to prevent potential harm to participants, including preventing breaches of confidentiality and maintaining participant anonymity (Creswell & Poth, 2018; Stake, 2010; Surmiak, 2018; Thurairajah, 2019). Participants were interviewed in 60 to 90-minute slots either before or after their standard work times at the site of their employment (Alase, 2017). When on-site interviews were not possible, remote phone interviews were conducted instead.

Research Method and Design

For the purposes of this study, a qualitative methodology with a case study design was utilized. This approach best fit with the stated goals and purpose of the study. Generally speaking, the purpose of qualitative research is to understand the essence of an experience by gathering data from witnesses and practitioners with direct knowledge of the phenomenon (Creswell & Creswell, 2018; Stake, 1995). By utilizing a single case study, the researcher worked to deeply understand a problem through the lens of a specific organization (Creswell & Poth, 2018; Denzin & Lincoln, 2011; Plumper et al., 2019). According to Grover et al. (2018) and Olufemi (2019), working directly with observers of a phenomenon can help provide the deep understanding that this study intends to achieve. Runeson et al. (2012) specifically noted the usefulness of qualitative case study research within the technological support industry. Overwhelmingly, researchers note that big data analytics support improved financial performance (Bajari et al., 2019; Lehrer et al., 2018; Muller et al., 2018; Popovic et al., 2018) but require the appropriate culture (Garcia-Perez, 2018; Halaweh & El Massry, 2015). The chosen research approaches are intended to support the study's overall purpose of understanding how organizations can adopt a culture of data-driven decision-making.

Discussion of Method

The selection of research methodology is deeply rooted in the researcher's typical or adopted worldview (Creswell & Poth, 2018; Denzin & Lincoln, 2011). According to Guba (1990), the worldview of a researcher is the core set of beliefs and assumptions about the nature of the world that direct the approach toward research. This research was concerned with developing an understanding of a phenomenon with very little preconceived notions or hypotheses regarding its nature. This indicates that the researcher was to adopt a constructivist worldview, which allows practitioners to perform research without the need for a strictly defined hypothesis (Creswell & Creswell, 2018; Stake, 1995). Constructivism is widely seen as a worldview that encourages deep understanding of a phenomenon and is an important building block of qualitative methodologies (Bettoni, 2018; Dean, 2018; O'Connor et al., 2018). Stake (1995) proposed that when working in a qualitative environment, researchers may conduct more open-ended investigation and exploration. This proposal is reiterated and echoed by Creswell and Creswell (2018), Korstjens and Moser (2017), and Kross and Giust (2019), especially in the arena of applied business research. This open-ended form of research requires that researchers understand the subjectivity of responses in the context of historical and social considerations (Creswell & Creswell, 2018; Stake, 1995). Understanding the ways in which organizations adopt a culture of data-driven decision-making requires the exploration and research designs afforded only by qualitative methods.

The qualitative method suited this study greatly. Stake (2010) stated that qualitative methodologies encourage holistic understanding and interpretation of a phenomenon. Creswell and Poth (2018) explained that qualitative researchers must inherently make four philosophical assumptions regarding the (a) ontological, (b) epistemological, (c) axiological, and (d) methodological nature of the world and research. These assumptions state that the world must be interpreted through the eyes of witnesses and the context of an environment, and that data gathered is always subjective and filtered through the values of the participant (Creswell & Poth, 2018). Such assumptions are made to allow researchers the freedom to investigate phenomena without the bounds of stringent quantitative methodologies (Creswell & Poth, 2018; Denzin & Lincoln, 2011; Guba, 1990). This research focused on understanding a movement within an organization and exploring the environment rather than measuring and objectively linking variables. Researching the ways in which organizations can develop and adopt a data-driven culture required working directly with members of an organization to document and interpret their experiences, an exercise that required qualitative inquiry (Annansingh & Howell, 2016; Denzin & Lincoln, 1998; Guillen, 2019).

Discussion of Design

For this study, the researcher aimed to construct a holistic theory regarding a business phenomenon by investigating its implementation in a particular environment. The purpose of this research was to explore the ways in which an organization can implement a culture of data-driven decision-making. Conceptually, Creswell and Poth (2018) and Denzin and Lincoln (2011) explained that case studies permit researchers to perform an in-depth investigation of a phenomenon within the context of a specific case. This suited the stated goals of achieving a holistic comprehension of data-driven cultures. Case study research results in thick descriptions of the factors and relationships between factors that lead to a particular outcome (Wynn & Williams, 2012). This design also proves helpful when current understandings of a phenomenon are (a) inadequate, (b) conflicting, or (c) contradictory toward modern research (Vissak, 2010).

Ridder (2017) described multiple approaches to conducting case study research, including (a) beginning with no theory, (b) beginning with a theory containing gaps and holes, (c) embarking upon a social construction of reality, and (d) discovering anomalies. Robert Yin, a pioneer of case study research, supports the “gaps and holes” theory proposed by Ridder (2017, p. 287). Robert Stake, another contemporary innovator in research design, aligns with the “social construction of reality” theory (Ridder, 2017, p. 288). This study aimed to follow the social construction theory of a case study due to (a) curiosity of the researcher, (b) its ability to provide thick description, and (c) the researcher’s pursuit of rounded understanding, all features of this theory (Ridder, 2017). Lokke and Sorensen (2014) explained that case study design regarding the generation of a theory is different than the design of a case study intended to test a theory. Pearse (2019) described this difference as inductive versus deductive qualitative research. For the purposes of this study, the researcher focused on building a theory rather than testing a specific hypothesis.

In defining processes by which qualitative researchers should conduct case studies in software engineering firms, Runeson et al. (2012) explained that such studies should be flexible enough to account for the dynamic and complex nature of software development. However, researchers must still be careful to only operate within the specific, defined boundaries of the study (Creswell & Poth, 2018). Findings and conclusions must be based on clear and diverse sources of evidence (Runeson et al., 2012). Yin (2018) suggested utilizing (a) interviews, (b) documents, (c) procedures, and (d) various other sources of evidence that can be used to support claims and new theories. In a case study focused on the information technology sector, research is considered valuable if it contributes to the existing body of knowledge, whether by discovering a new theory or expanding upon an old (Runeson et al., 2012). Researchers in qualitative case studies must be careful to conduct research that is generalizable beyond the scope of the current study (Lincoln & Guba, 1985; Plumper et al., 2019).

Summary of Research Method and Design

Utilizing a qualitative case study best supported the planned purpose of this research. Possessing a deep understanding of a phenomenon—specifically how business can create a culture of data-driven decision-making—is the cornerstone of qualitative research (Creswell & Creswell, 2018; Stake, 1995) and, to a lesser extent, case studies (Creswell & Poth, 2018; Denzin & Lincoln, 2011). To generate a theory that can be used to describe a culture transformation, the researcher adopted Stake's theory of social constructivism (Ridder, 2017). Procedures outlined by Lokke and Sorensen (2014) for generating a theory were used to separate the study from those intended to test a particular hypothesis. Maintaining (a) a flexible environment, (b) a wide and diverse body of research, and (c) a commitment to contributing to the existing body of research improved the usefulness of this study and credibility of its results (Runeson et al., 2012).

Population and Sampling

The population for this qualitative case study was the group of all transportation organizations in the southern United States. According to Yin (2018), the participants in a case study are the cases themselves. Sampling methodologies take on a new dynamic within qualitative research because researchers intend to obtain a deep understanding of a phenomenon rather than its pervasiveness (Yin, 2018). Creswell and Poth (2018) recommended purposive sampling methodologies, stating that this allows the researcher to control the context under which the study is performed. Purposive methodologies encourage researchers to select participants based on their anticipated usefulness in answering the research questions of interest (Gentles et al., 2015). Applying a purposive method to individuals selected for participation, Creswell and Poth (2018) suggested using maximum variation sampling strategies that allow researchers to find participants with a diverse set of backgrounds who may provide unique insight and perspectives.

Discussion of Population

In a study intended to understand how transportation companies in the southern United States can implement cultures of data-driven decision-making, the highest-level population would be the companies in scope. Asiamah et al. (2017) described this group as the general population, or the group of all entities with a stake in the area of interest. This scope is then narrowed to the target population, a subset of the general population that satisfies the selection criteria established in a study (Asiamah et al., 2017). In this case, eligible organizations were required to (a) be a medium-sized operation of between 500 and 2500 active units, (b) employ more than 100 but less than 500 office staff, (c) employ at least 75% of implementation team members in-house, and (d) have adopted or are in the process of adopting data-driven technologies. For this single case study, one organization was identified; 18 to 20 individual participants employed by the organization were then identified and recruited for participation. Alase (2017) contended that selection criteria must ensure that participants are selected carefully and limit the potential individuals or organizations to those who can provide meaningful data. Asiamah et al. (2017) limited populations further by narrowing the scope to the accessible population, a group of entities within the target population who are willing and able to participate in the research study.

Presently, the transportation industry in the United States is offered many opportunities with regard to smarter technologies (Chai et al., 2017; Demirova, 2017; Heilig et al., 2017; Parra-Romero et al., 2017; Prokudin et al., 2018). However, the organizations are frequently unable or unwilling to implement such technology (Alameen et al., 2016; Roth, 2016). The industry experiences high turnover, particularly within the driving workforce (Miller et al., 2017). Transportation often sees very thin margins, poor performance, and low morale (Miller et al., 2017). Sersland and Nataraajan (2015) demonstrated that these trends are not limited to a particular organization, region, or even timeframe. Because of the toughness of the industry, organizations often forsake initiatives that do not have an immediate, direct impact on financial performance; this frequently includes advances in technology (Alameen et al., 2016; Roth, 2016). When organizations are able to generate enough capital to invest in technology, this investment is often unsustainable due to a lack of culture surrounding and supporting their initiatives (Olufemi, 2019).

This study required the researcher to seek an organization or organizations capable of and willing to commit to the implementation of a culture of data-driven decision-making. The general population was the set of transportation companies in the American south. The target population as defined by Asiamah et al. (2017) was the subset of medium-sized organizations with the goal of becoming data-driven. Finally, the accessible population referred to the subset of these businesses who are willing to work with the researcher to identify the ways in which they have become or are becoming data-driven in their operations.

Discussion of Sampling

Researchers tend to agree that sampling strategies differ significantly between quantitative and qualitative studies (Alase, 2017; Creswell & Poth, 2018; Yin, 2018). Whereas a quantitative methodology would often require researchers to utilize randomized methods of sampling, qualitative studies are more aligned with purposive sampling (Creswell & Poth, 2018; Yin, 2018). According to Creswell and Poth (2018), purposive sampling allows researchers to select cases or participants that are more likely to provide useful information. Using a narrow and traditional definition of sampling, Yin (2018) argued that the process in a qualitative case study is non-existent. Purposive methods may include (a) maximum variation, (b) homogeneous, (c) snowball, or (d) convenience sampling, among others (Creswell & Poth, 2018). Runeson et al. (2012) showed that sampling in a qualitative study, especially in the information technology sector, must be intentional. Researchers are careful to explain that purposive methods do not compromise the integrity of the study; such methods instead allow researchers to be deliberate about their participants and perform a study in a particular context (Alase, 2017; Creswell &

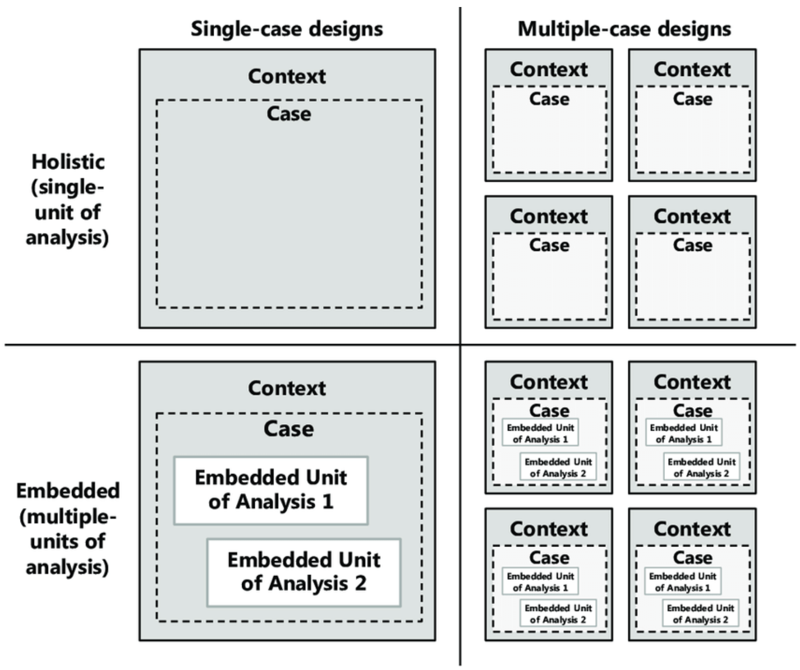
Poth, 2018; Gentles et al., 2015; Runeson et al., 2012; Yin, 2018). Researchers performing qualitative case studies should select participants based on the likelihood that their knowledge and experience can provide meaningful and relevant data with respect to specific research questions (Alase, 2017; Gentles et al., 2015; Suen et al., 2014).

Researchers warn that purposive sampling is not analogous to convenience sampling and explain that such a methodology may result in unintended consequences (Suen et al., 2014). Convenience sampling bypasses establishing a target population and leads to potentially non-generalizable results and carries a higher burden of reliability (Suen et al., 2014). Instead, purposive sampling is intended to give researchers the ability to seek inimitable participants who can provide unique, rich descriptions of their relevant experiences (Alase, 2017; Gentles et al., 2015; Suen et al., 2014). Alase (2017) explained that participants should have experience with the phenomenon of interest and that, since the intent of qualitative research is to understand a particular experience, purposive sampling and choosing individuals with intimate knowledge of the experience is in the best interest of the study. Ishak and Abu Bakar (2014) observed that researchers in qualitative studies are not obligated to experience a rigorous randomization sampling process and that randomized sampling inhibits the richness of data gathered.

Yin (2018) explained that researchers for a case study, whether planning on a single case or multiple case study, must decide between a holistic or embedded design. According to Ishak and Abu Bakar (2014), Runeson et al. (2012), and Yin (2018), holistic designs treat a business as a single unit and results are globalized. Embedded designs, by contrast, require researchers to evaluate individual subunits (Ishak & Abu Bakar, 2014; Runeson et al., 2012; Yin, 2018). Yin's (2018) case study design framework is reproduced in Figure 2. For this study, subunits are easily identifiable, and an embedded approach is preferred. A purposive methodology toward an embedded design is the choice sampling strategy for this research, based on the theories set forth by Alase (2017), Creswell and Poth (2018), Runeson et al. (2012), and Yin (2018).

Figure 2

Basic Case Study Designs



Note. Adapted from *Case study research and applications: Design and methods* (6th ed.) by Yin, 2018, p. 48. Copyright 2018 by Sage Publications. Reprinted under express permission from publisher (see Appendix E).

Once the (a) population and sample frame, (b) sampling methodology, and (c) nature of the case study design have been established, researchers must determine the appropriate sample size (Ishak & Abu Bakar, 2014; Suen et al., 2014). For results to be as accurate and well-rounded as possible, researchers must reach a saturation point in data gathering (Ishak & Abu Bakar, 2014). The sample size, therefore, is based on the amount of data required to reach saturation (Suen et al., 2014). Often, case study sample sizes are inadequately small, with researchers defending their samples by claiming saturation of the data or pragmatic justifications (Vasileiou et al., 2018). According to van Rijnsoever (2017), saturation is reached only after observations have deeply covered all codes. Qualitative researchers can make use of a minimalist strategy in which participants are selected only when they provide new insights or avenues of investigation (van Rijnsoever, 2017).

Much research has been performed to understand how saturation can be achieved when participants are difficult to locate or recruit (Alase, 2017; Geddes et al., 2018; Ishak & Abu Bakar, 2014; Marcus et al., 2017). Some researchers suggest expanding the study to a wide group of potential participants instead of a deep analysis into an organization, though this methodology risks reliability (Geddes et al., 2018). Alase (2017) and Ishak and Abu Bakar (2014) proposed using a snowball strategy to expand to further participants. Under this strategy, existing participants can recruit others in their organization, providing access that may previously have been denied (Alase, 2017; Ishak & Abu Bakar, 2014). This strategy has flaws as well, primarily receiving criticism for bias or fabrication of data when new recruits are under additional organizational constraints (Marcus et al., 2017). To achieve further saturation, participants, especially organizational elites, can be targeted through social and professional media for recruitment into the research (Maramwidze-Merrison, 2016).

Researchers can use one or more methodologies to discover the point at which saturation is reached (Fusch et al., 2018; Saunders et al., 2018; Weller et al., 2018). Saunders et al. (2018) described four methodologies, including noticing when participants repeat (a) categories, (b) themes, (c) exemplifications of themes in data, and (d) data itself. According to Fusch et al. (2018), researchers can be more proactive in setting saturation thresholds by triangulating participants in the scopes of (a) data, (b) investigators, (c) theories, or (d) methodologies. Weller et al. (2018) provided a mathematical approach, defining saturation as the point at which participants provide, on average, less than one new item of interest.

Summary of Population and Sampling

This qualitative case study offered a population of transportation companies in the southern United States and permitted a methodology of purposive sampling. The research theories discussed allowed the researcher to define sampling criteria and select an organization that best embodied the needs of the study (Creswell & Poth, 2018; Gentles et al., 2015; Yin, 2018). Within the particular case, an embedded approach was used, necessitating the recruitment of 20 or more diverse individuals to the study. The sample size was determined by the anticipated saturation point of data, consistent with the theories of Ishak and Abu Bakar (2014) and Suen et al. (2014).

Data Collection

In a qualitative research study, the primary instrument of data collection is the researcher (Alase, 2017; Clark & Veale, 2018). The researcher is ultimately responsible for collecting all data and is a filter through which all data must flow (Xu & Storr, 2012). Arsel (2017) explained that researchers should use interview guides when working with participants to ensure that conversations remain focused on the problem statement and research questions involved with the study. Procedures were defined for the researcher of this study to follow while conducting interviews, including the ways in which data were captured and stored in computer-assisted qualitative data analysis software, as suggested by Woods et al. (2016) and Yakut Cayir and Saritas (2017). Finally, the coding process was defined, which allowed the researcher in the study to determine common themes throughout the responses of multiple participants (Williams & Moser, 2019).

Instruments

An instrument in an academic research study is a medium or tool through which data are gathered (Xu & Storr, 2012). Due to the qualitative nature of this study, the primary instrument behind the collection and analysis of data was the researcher (Clark & Veale, 2018). Xu and Storr (2012) stated that in quantitative research, instruments objectively measure variables of interest. By contrast, the researcher in a qualitative study is the instrument by which all data and information must be collected and interpreted (Alase, 2017). Therefore, it is the responsibility of the researcher to be skilled in interpretive thinking and remain focused during data collection (Clark & Veale, 2018). Because the primary goal of qualitative research is to explore the essence of an experience, the researcher must adopt the right mindset when collecting data as the primary instrument (Alase, 2017). An improper worldview leads to weak data collection techniques and affects the quality of the final analysis (Alase, 2017; Xu & Storr, 2012). The researcher in a qualitative case study should adopt a constructivist mindset, building from the proper ontological and epistemological philosophical assumptions that lead to a strong researcher as an instrument (Xu & Storr, 2012). Because the idea of researcher as an instrument is a fundamental assumption of qualitative research, all data filters through the researcher (Xu & Storr, 2012). This fact of qualitative research indicates that researchers should be careful not to impose their own views and that researchers should allow the participants themselves to generate themes and ideas (Alase, 2017).

In designing an interview, researchers should be careful to keep discussions on track but allow enough flexibility to explore new and emerging themes (Arsel, 2017; Guest et al., 2017; Pedersen et al., 2016). To develop a proper interview guide, researchers must possess a certain level of knowledge about the topic of interest (Pedersen et al., 2016). If researchers are unable to create a suitable interview guide, focus groups may be used to elicit themes from larger groups of individuals (Guest et al., 2017; Pedersen et al., 2016). According to Guest et al. (2017), focus groups result in less diverse ideas, but provide a high-level overview of the topics that may be explored in individual interviews. Individual interviews consistently generate more specific themes (Guest et al., 2017).

When deciding on a structure for interviews with individual participants, Arsel (2017) stated that researchers should avoid falling into the trap of designing a completely unstructured interview. This, Arsel (2017) claimed, is the research equivalent of searching for a “needle in a haystack” (p. 940). Alase (2017) instructed researchers to follow a semi-structured interview approach and to design interviews of between 60 and 90 minutes in duration. A loose guide of interview questions designed with ultimate research questions in mind allows researchers to pursue new, emerging themes while keeping interviews within the bounds of the qualitative study (Arsel, 2017). Researchers should be careful not to permit conversations to stray too far from the stated research questions, especially when interviewing assertive or elite participants (Lancaster, 2017). Such participants often attempt to gain improper control over the study, often by suppressing the participation of others or by emphasizing their own viewpoints over those of others (Lancaster, 2017). Interviewers should use a pre-developed interview guide to keep conversations on track and to elicit the most useful information during their limited time with participants (Alase, 2017; Arsel, 2017; Lancaster, 2017).

An interview guide for this qualitative study is included in Appendix F. This interview guide contains opening and closing statements, as well as all in-scope interview questions. The questions supported one of the three main research questions, which ask (a) what constitutes a data-driven culture, (b) what specific actions and initiatives organizations can undertake to introduce or support this culture, and (c) how businesses can improve data maturity by shifting decision-making power toward technology. The interview questions, as explained by Arsel (2017), must support one or more of the research questions. Some questions, such as questions 1, 2, 8, 9, and 11, addressed the definition of a data-driven culture and what constitutes a data-mature organization by probing the participants' views on the appropriate target culture. Other interview questions, including 3, 4, 5, 10, and 14, addressed the ways organizations can transform their culture by exploring participants' understandings of the specific actions they must take to implement a culture of data-driven decision-making. Finally, questions such as 6 and 13 focused on how organizations can become more mature by asking how organizational elites can be recruited and transformed into champions of data-driven initiatives. Each of these questions addressed the original problem statement, which stated that organizations are often unable to implement data-driven cultures despite their possession of technical capabilities (Bogdan & Lungescu, 2018; Galbraith, 2014; Grover et al., 2018; Olufemi, 2019).

Data Collection Techniques

The primary avenues of data collection were (a) interviews, (b) observations, and (c) surveys conducted among employees of a single organization. Moser and Korstjens (2018) suggested a loosely defined strategy of data collection while identifying (a) observations, (b) face-to-face interviews, and (c) focus groups as potential sources of data. Yin (2018) explained that a case study comprises four principles of data collection, including (a) triangulation of data sources, (b) creating a database to store information, (c) maintaining an appropriate evidentiary chain, and (d) properly using information gathered from social media sources. During the interview process, the researcher followed the suggestions of Alase (2017), which state that interviews should be (a) semi-structured, (b) limited to 60 to 90 minutes, and (c) initially limited to one interview per participant. The site and time of each interview or observation were ultimately left for the participants to decide, although interviews occurring at their typical work site were preferred. Due to the 2020 COVID-19 outbreak, interviews sometimes occurred via teleconferencing technologies. The researcher used the interview guide in Appendix F as a handbook for conducting each session, consistent with the suggestions of Alase (2017), Arsel (2017), and Lancaster (2017).

During each interview, the researcher limited interjections and minimized the introduction of new themes and preconceptions into the conversation; allowing participants to introduce claims through conversation results in the most accurate qualitative data (Alase, 2017). Clark and Veale (2018) explained that the interviewer must minimize their own assumptions and biases during discussions with participants. The interviewer must also remain focused on collecting data during this phase, ensuring that all interview topics are addressed (Clark & Veale, 2018). During interviews, researchers must consider that the ultimate goal of each subsequent interview is reaching a point of saturation (Ishak & Abu Bakar, 2014; Suen et al., 2014; van Rijnsoever, 2017).

With the consent of both the site and individual participants, interviews were each recorded using two different devices to account for potential technological failures. These devices included the researcher’s primary computer and cellular device. These devices were kept secure and all identifying information was destroyed once interviews were transcribed. Furthermore, the researcher took notes regarding emerging themes using traditional notebooks (Alase, 2017). Following each interview, the researcher transcribed discussions and worked to keep participants anonymous. At this point, the researcher transitioned to the data organization and analysis processes.

Data Organization Techniques

For this qualitative research study, the researcher used a mixture of traditional and modern methods for organizing data gathered through interviews and observations. As a primary principle of data collection, Yin (2018) suggested creating a qualitative case study database that can be used to organize information gathered in interviews and observations. Yin (2018) stated that documents should be clearly identified and separated into raw data and report categories. Information stored in a qualitative database should be divided into (a) notes, (b) documents, (c) tabular models, and (d) narrative compilations (Yin, 2018). Organizing information in a well-defined and orderly database allows researchers to more easily complete coding and analysis later in the research process (Alase, 2017; Vaughn & Turner, 2016).

Creswell and Poth (2018) explained that computer software can be used to take the place of traditional file systems and handwritten notes. Although such software cannot perform all analysis for researchers, programs may be of assistance in the storage and organization of information (Creswell & Poth, 2018). Database software allows researchers to efficiently organize documents and other sources of data (Woods et al., 2016; Yakut Cayir & Saritas, 2017). Alase (2017) recommended storing information in secure locations. Creswell and Poth (2018) stated that researchers utilizing technology in their data organization should prioritize data security and safety, emphasizing the need for masking sensitive information and keeping duplicate copies of data in multiple locations. The researcher in this qualitative study organized interview transcripts and other data sources in files on a password-protected computer, which was replicated to a secure cloud file storage solution in the case of computer failure. Files, including documents and transcripts, were imported to a reputable software solution (Woods et al., 2016; Yakut Cayir & Saritas, 2017). Within this software, data were organized with metadata such as (a) a unique but anonymous participant identifier, (b) the time of the interview, and (c) the location of the observation.

Summary of Data Collection

As the primary instrument by which data are collected in a qualitative research study, the researcher must be careful to play a proper role in the data collection process (Alase, 2017; Clark & Veale, 2018; Xu & Storr, 2012). While conducting interviews for this research study, the researcher used the interview guide included in Appendix F (Arsel, 2017). This interview guide was intended to maintain the integrity of the data collection process by ensuring that the interviewer gathered data that specifically answers the research questions and satisfied the purpose statement (Arsel, 2017). Data were stored and organized in reputable qualitative database software to secure and maintain transcripts (Woods et al., 2016; Yakut Cayir & Saritas, 2017). Raw data were kept apart from report documents (Yin, 2018). Metadata were applied to each article of information defining when and where the information was obtained.

Data Analysis

Creswell and Poth (2018) explained that the major stages of data analysis involve (a) organizing data, (b) coding information, (c) organizing codes into themes, and (d) representing and interpreting the data. The analysis phase of qualitative research constitutes the transformation of data into manageable themes and trends that can be used to represent the essence of participant experiences (Clark & Veale, 2018; Creswell & Poth, 2018). Yin (2018) described four strategies researchers may use to work through data analysis, suggesting that case study researchers (a) depend on theoretical philosophies, (b) build themes from the ground up, (c) advance a description of the case, or (d) consider alternative explanations. After selecting a data analysis strategy, researchers may employ one or more analysis techniques such as (a) matching patterns, (b) building explanations, (c) analyzing content over time, (d) building logic models, or (e) synthesizing information across multiple cases (Yin, 2018). Speaking generally, Mayer (2015) described qualitative data analysis as a data reduction process. Researchers overwhelmingly support coding as a chief tool of data analysis, with many experts encouraging researchers to follow (a) open, (b) axial, and (c) selective coding practices (Alase, 2017; Moser & Korstjens, 2018; Richards & Hemphill, 2018; Williams & Moser, 2019).

Coding Process

To reduce lengthy transcripts to manageable themes describing the essence of an experience, as Mayer (2015) stated, researchers should follow a coding process. Many qualitative researchers fall into the trap of utilizing anecdotal evidence from interviews and survey responses to support the results of studies (Vaughn & Turner, 2016). Instead, researchers should use coding methods to systematically review transcripts and identify themes that run through the responses of a greater number of participants (Vaughn & Turner, 2016). Belotto (2018) referred to codes, the results of the coding process, as units of meaning. Such codes allow researchers to interpret and represent large segments of text and determine how themes are related to one another (Belotto, 2018). Due to the iterative nature of qualitative research, Moser and Korstjens (2018) explained that researchers should perform qualitative analysis in the midst of collecting additional data. Moving between the (a) sampling, (b) data collection, and (c) data analysis stages of research allows researchers to code information while affording the option to further explore themes discovered in analysis (Moser & Korstjens, 2018). Once this process has been completed, researchers were able to explain what themes exist in the data and further understand the essence of the topic of interest (Belotto, 2018; Clark & Veale, 2018; Creswell & Poth, 2018; Moser & Korstjens, 2018).

Alase (2017) identified three distinct stages of the coding process, suggesting that researchers (a) code responses into large portions of conversations, (b) reduce such responses to only the essence of the response, and (c) reduce again to only a phrase or category. Researchers frequently describe these stages as (a) open coding, (b) axial coding into categories, and (c) selective coding into a small number of themes (Moser & Korstjens, 2018; Richards & Hemphill, 2018; Williams & Moser, 2019). Expanding on the open-axial-selective methodology, Richards and Hemphill (2018) instructed researchers to conduct preliminary organization of data and perform open and axial coding tasks. The writers then support additional steps, including (a) developing a codebook, (b) conducting pilot tests, (c) performing selective coding, and (d) reviewing and finalizing the themes elicited from the data (Richards & Hemphill, 2018). Following an expanded process that encourages participant and reader feedback improves the reliability and trustworthiness of the final analysis (Creswell & Poth, 2018; Richards & Hemphill, 2018; Yin, 2018).

When undertaking coding procedures, researchers should be careful to remember their driving purpose statement and research questions (Belotto, 2018). In the open coding phase, Williams and Moser (2019) suggested attaching categories to text that answer questions following the 5W-1H approach, or questions beginning with (a) who, (b) what, (c) when, (d) where, (e) why, or (f) how. Clark and Veale (2018) summarized that open coding allows researchers to assign categories to long passages of text in transcripts or other sources of information. This approach permits researchers to identify major emergent themes within the text that may be used in deeper analysis in later stages of analysis (Williams & Moser, 2019). To improve the quality and relevance of the analysis, Belotto (2018) implored researchers to use only codes that can be related to the research questions. In axial coding, researchers should identify connections between themes found during the open coding phase (Richards & Hemphill, 2018). According to Williams and Moser (2019), axial coding is intended to (a) refine, (b) align, and (c) categorize the ideas uncovered during the initial coding tasks. During selective coding, researchers must identify and sort categories and themes that provide meaning in the context of the research questions (Williams & Moser, 2019). At this stage, patterns take form and researchers may characterize and relate themes according to their (a) similarities, (b) differences, (c) frequency, (d) sequence and order, (e) correspondence and relationships, or (f) causation (Clark & Veale, 2018). Following these coding procedures gives representation to all responses and ensures inclusion of all perspectives when conducting analysis (Clark & Veale, 2018; Creswell & Poth, 2018; Vaughn & Turner, 2016).

Completing the aforementioned coding processes by hand or maintaining manually in a notebook can be an unnecessarily labor-intensive and time-consuming process (Yakut Cayir & Saritas, 2017). Modern technology affords many opportunities for researchers to streamline the data organization process through a paradigm known as computer-assisted qualitative data analysis, or CAQDAS (Yakut Cayir & Saritas, 2017). Software such as (a) ATLAS.ti, (b) HyperRESEARCH, (c) MAXQDA, or (d) NVivo are modern examples of programs that allow users to (a) organize data, (b) code responses, (c) identify themes, and (d) report results (Yakut Cayir & Saritas, 2017). Woods et al. (2016) warned that although CAQDAS software enhances the data organization and analysis process, it may also weaken researcher reflexivity and negatively impact ongoing data collection. Researchers should be careful to avoid defining research around the capabilities of software and to now allow software to undermine their own reflexivity (Woods et al., 2016).

Computer-assisted analysis allows researchers to more efficiently organize and analyze the results of interviews and other sources of data (Woods et al., 2016; Yakut Cayir & Saritas, 2017). Experimental methodologies exist that can further assist coding by performing much of the work for researchers (Estrada, 2017; Rose & Lennerholt, 2017). Artificial intelligence algorithms can scan transcripts and process meanings into a number of themes without researcher intervention (Rose & Lennerholt, 2017). Estrada (2017) showed that free, open source technologies such as the R programming language can be used to perform such analyses. Cabrera and Reiner (2018) suggested assigning quantitative data summaries to codes to understand frequencies that can be used in further content analysis. Although not a comprehensive solution for data analysis, these methodologies were of use in this study.

For this study, the researcher used RQDA CAQDAS software to perform coding and other analysis tasks (Creswell & Poth, 2018; Woods et al., 2016; Yakut Cayir & Saritas, 2017; Yin, 2018). As with data collection, information was stored on a password-protected computer and replicated to cloud file storage to prevent accidental data loss. The researcher used CAQDAS software to code transcripts and elicit themes from the data, following the methodologies proposed by Alase (2017) and Williams and Moser (2019). The researcher began by performing open coding and only including themes that supported the primary research questions (Belotto, 2018). Axial coding was then used to refine categories into interrelated themes (Richards & Hemphill, 2018; Williams & Moser, 2019). The researcher then identified selective codes that provided deeper meaning and adequately represented all ideas identified through data collection (Clark & Veale, 2018; Creswell & Poth, 2018; Vaughn & Turner, 2016). Finally, the researcher used experimental methodologies mentioned by Estrada (2017), such as the R programming language, to confirm themes and discover any potentially missed ideas discussed in the transcripts. The researcher performed these tasks concurrently with the sampling and data collection phases, consistent with the recommendations of Moser and Korstjens (2018).

Summary of Data Analysis

The researcher was responsible for reducing data into manageable themes identified through the data analysis process (Mayer, 2015). Following a defined coding process ensures that researchers provide representation to all perspectives uncovered through data collection, rather than a select few (Clark & Veale, 2018; Creswell & Poth, 2018; Vaughn & Turner, 2016). Data should be organized and analyzed using (a) open, (b) axial and (c) selective coding processes (Alase, 2017; Moser & Korstjens, 2018; Richards & Hemphill, 2018; Williams & Moser, 2019). Researchers should ensure that codes adhere to the stated purpose statement and research questions (Belotto, 2018). CAQDAS software can be used to assist researchers in the coding process, though researchers must be careful to maintain the integrity of the research (Woods et al., 2016; Yakut Cayir & Saritas, 2017). Experimental techniques defined by Estrada (2017) and Rose and Lennerholt (2017) can further support data analysis, though these must be used only to supplement more traditional and tested methods. Codes and themes identified through the data analysis process were transformed into analyses that were described in context in the final report (Alase, 2017).

Reliability and Validity

Researchers should strive to conduct field studies and present findings in ways that convey the accuracy and truthfulness of their findings. The reliability of a qualitative case study can be established through demonstrating replicability of the study (Belotto, 2018; Yin, 2018). Validity may be established through research tasks and processes and is frequently referred to as the trustworthiness of findings (Amankwaa, 2016; Dennis, 2018; Kornbluh, 2015; Korstjens &

Moser, 2018; Lincoln & Guba, 1985). To improve reliability, researchers should follow standardized protocols, which may include the development of interview guides and maintaining codebooks (Alase, 2017; Arsel, 2017; Lancaster, 2017; Richards & Hemphill, 2018). Researchers may validate their findings and convey validity to readers by (a) achieving construct validity through saturation, triangulation, and member-checking (Alase, 2017; Fusch & Ness, 2015; Kornbluh, 2015; Saunders et al., 2018); (b) reaching internal validity by spending extended periods of time in the field, using standard logic models, and addressing rival opinions (Creswell & Creswell, 2018; Creswell & Poth, 2018; Yin, 2018); and (c) supporting external validity through applying thick description (Fusch et al., 2018).

Reliability

Qualitative researchers should ensure that studies can be repeated by others, operating in a similar context, with the same results (Yin, 2018). Demonstrating replicability by documenting the research process before, during, and after the field study helps convey a sense of reliability to readers (Yin, 2018). Belotto (2018) explained that when two researchers work independently on studies with identical or similar research questions, the individuals often uncover different themes. Despite reviewing the same literature and conducting interviews under the same context, researchers can arrive at different codes and opposing conclusions (Belotto, 2018). Providing documentation at all stages of the research process is crucial to supporting replicability and reliability (Belotto, 2018). Mendes-Da-Silva (2019) observed that some researchers, particularly those under intense pressure to publish results, sometimes introduce a degree of bias or inflate the importance of certain variables to craft a more interesting narrative. Although such practices sometimes improve the chances of being published in an elite journal, these so-called benefits are responsible for the erosion of reliability within the study (Mendes-Da-Silva, 2019). Aguinis and Solarino (2019) explained that replicability requirements force a degree of transparency between the researcher and reader that results in ethical practices and reliable research.

Following a standardized case study protocol improves reliability of a qualitative case study (Yin, 2018). This frequently refers to (a) developing an interview guide, (b) populating a case study database, and (c) maintaining a chain of evidence (Alase, 2017; Arsel, 2017; Lancaster, 2017; Yin, 2018). When conducting data collection tasks, researchers should utilize an interview guide that ensures interviews are conducted consistently (Arsel, 2017; Lancaster, 2017). This is especially important in case studies involving multiple researchers (Yin, 2018). Reliability procedures are not limited to data collection methods; researchers should follow a well-documented and consistent procedure for data analysis as well (Belotto, 2018; Creswell & Poth, 2018; Roberts et al., 2019). Researchers can establish consistent, reliable procedures by introducing a codebook that informs themselves and their co-researchers of what codes have been selected (Creswell & Poth, 2018; Richards & Hemphill, 2018). Maintaining a well-defined codebook improves rigor and reliability within a qualitative research study (DeCuir-Gunby et al., 2011; Roberts et al., 2019). When creating a codebook, researchers should (a) perform open coding, (b) identify themes within samples, (c) compare themes within each sample, (d) identify specific codes through selective coding, and (e) evaluate reliability (Boyatzis, 1998). Saldana (2015) stated that qualitative research can be considered reliable if the final list of codes reaches a reliability threshold (defined as the percent of codes on which independent researchers would agree) of 75%.

To ensure reliability within this study, the researcher conducted data collection using the interview guide provided in Appendix F. This ensured reliable interview procedures that, under a similar context, should result in replicable results (Arsel, 2017; Lancaster, 2017). Data organization occurred within reputable CAQDAS software that enabled efficient and orderly storage of data (Vaughn & Turner, 2016; Woods et al., 2016; Yakut Cayir & Saritas, 2017). Data analysis followed the coding processes defined by Williams and Moser (2019) with all layers of coding (open, axial, and selective) being documented in a codebook (Boyatzis, 1998; DeCuir-Gunby et al., 2011; Roberts et al., 2019; Saldana, 2015). This codebook is provided in Appendix G. Following these procedures closely resulted in reliable research that maintains replicability across studies bounded by the same context (Aguinis & Solarino, 2019; Belotto, 2018; Yin, 2018).

Validity

Researchers strive to ensure that their publications are accepted as valid (Kornbluh, 2015). When a decision is made to accept assertions as true, the decision-maker has inherently and subtly evaluated the validity of a statement and decided that all validation criteria has passed (Dennis, 2018). Validity of qualitative research can be established through the research process (Amankwaa, 2016; Dennis, 2018). According to Kornbluh (2015), trustworthiness of qualitative research is determined by how well the researcher's analysis reflects the experiences and beliefs of participants. Ensuring the validity of research requires that researchers complete various validation tasks across several dimensions of trustworthiness (Amankwaa, 2016). Trustworthiness can be divided into multiple dimensions, notably credibility, transferability, dependability, and confirmability (Lincoln & Guba, 1985). Ultimately, the validity of a qualitative research study is rooted simply in whether or not it can be trusted (Korstjens & Moser, 2018).

Yin (2018) defined three forms of validity, including construct, internal, and external validity. According to Fusch et al. (2018), construct validity refers to the extent to which a study’s results can be connected to its conceptual framework. Yin (2018) elaborated, stating that studies that have construct validity measure the correct concepts under the stated research questions. Qualitative researchers should explain to readers how their data and analysis connects to the topics purported to be in scope (Fusch et al., 2018). In comparison, internal validity connects data to findings and refers to a study’s ability to establish causality between themes (Yin, 2018). External validity describes the ability to transfer findings to a similar but independent context (Fusch et al., 2018; Yin, 2018). Some researchers prefer to define external validity as a study’s generalizability (Yin, 2018), while others prefer to describe such validation as the study’s transferability (Fusch et al., 2018).

Researchers may employ various strategies when establishing validity in a qualitative study. To corroborate construct validity, studies must (a) achieve saturation and triangulation, (b) afford participants the chance to review findings, and (c) acknowledge and clarify biases (Alase, 2017; Creswell & Creswell, 2018; Creswell & Poth, 2018; Fusch & Ness, 2015; Kornbluh, 2015; Saunders et al., 2018; Yin, 2018). Reaching saturation requires researchers to adequately cover all codes, signified by repetition of categories or themes or by a lack of new codes in subsequent interviews (Saunders et al., 2018; van Rijnsoever, 2017; Weller et al., 2018). Fusch and Ness (2015) explained that a lack of saturation is a major detriment to research validity. Furthermore, research must be diverse and make use of various sources of information (Yin, 2018). This form of validation is frequently referred to by researchers as triangulation (Alase, 2017; Creswell & Creswell, 2018; Creswell & Poth, 2018; Fusch et al., 2018). Obtaining a diverse set of sources and interview participants improves the depth of analysis, reduces risk, and provides researchers with their best opportunity of adequately satisfying the purpose of the study (Fusch et al., 2018). Researchers may also demonstrate construct validity by conducting member-checking with key participants (Alase, 2017; Kornbluh, 2015; Yin, 2018). Working with knowledgeable participants to verify analysis and study a draft report improves the credibility of the research (Creswell & Creswell, 2018; Creswell & Poth, 2018; Yin, 2018). This ensures that researchers understand the intended meanings of data provided by participants throughout the interview process (Kornbluh, 2015; Lincoln & Guba, 1985). Finally, construct validity is improved when researchers acknowledge their own biases and disclose to readers (Creswell & Creswell, 2018; Creswell & Poth, 2018).

Internal validity ensures that assertions made in a research study, as well as causality between themes, can be logically backed by data (Yin, 2018). Researchers must establish a clear path from data to codes and then to conclusions, a feat that may be accomplished by utilizing conventional logic models or pattern matching (Yin, 2018). Additionally, researchers may improve validity by conducting a prolonged engagement with participants (Creswell & Creswell, 2018; Creswell & Poth, 2018). This results in extensive field time and gives readers a sense of comfort with the validity of assertions (Creswell & Creswell, 2018; Creswell & Poth, 2018). According to Yin (2018), researchers are often tempted to suppress rival or dissenting opinions. Instead, researchers should address these views and explain how they impacted the data analysis or why they were excluded from consideration (Yin, 2018). Furthermore, acknowledgement of disconfirming evidence lets readers know that all viewpoints were considered during the analysis phase (Creswell & Creswell, 2018; Creswell & Poth, 2018).

Unlike construct and internal validity, external validity emphasizes the theory of qualitative research and downplays the direct involvement of the researcher (Yin, 2018). External validity determines whether or not findings can be generalized to a similar context but beyond the specific scope of the study (Fusch et al., 2018; Yin, 2018). Because the nature of external validity inherently requires comparison to future, unperformed studies, its evaluation must be completed by readers and future researchers (Fusch et al., 2018). Future researchers must assess a study's application in relation to the context of their own studies (Fusch et al., 2018). Researchers can assist readers in making their determination by applying thick description (Creswell & Creswell, 2018; Creswell & Poth, 2018). Under this methodology, researchers provide thorough documentation and explanation of context and findings, giving readers a deep understanding of the context in which the study was conducted (Creswell & Creswell, 2018; Creswell & Poth, 2018).

For this study, the researcher addressed construct, internal, and external validity by using several of the methodologies discussed in the literature. To improve construct validity, the researcher ensured that saturation was reached by documenting the coding process throughout data collection and noting when codes are repeated or when no new codes are discovered (Saunders et al., 2018; van Rijnsoever, 2017; Weller et al., 2018). The researcher also worked to triangulate sources of data by identifying participants from diverse segments of the organization (Alase, 2017; Fusch et al., 2018). This ensured that analysis is complete and adequately represents all viewpoints (Fusch et al., 2018). Though identifying traits were removed to ensure participant privacy and anonymity, generic job titles and responsibilities were divulged to demonstrate triangulation. To further supplement construct validity, 10-minute review sessions, or member checks, were conducted with participants to allow them to review findings and verify assertions (Alase, 2017; Kornbluh, 2015; Lincoln & Guba, 1985; Yin, 2018). To address internal validity, the researcher documented the extent of field time to demonstrate a prolonged engagement (Creswell & Creswell, 2018; Creswell & Poth, 2018). Furthermore, all assertions were backed by data and major points were addressed through charts or figures (Yin, 2018).

Dissenting opinions were addressed in the paper and all viewpoints were considered; those that were excluded from analysis were discussed and explanations for their exclusion were noted (Yin, 2018). Finally, when describing the context under which research was conducted, the researcher utilized thick description to empower readers to make a determination regarding external validity (Creswell & Creswell, 2018; Creswell & Poth, 2018; Fusch et al., 2018).

Summary of Reliability and Validity

Establishing reliability and validity with readers is critical to producing a believable and high-quality case study. Demonstrating replicability can support reliability (Belotto, 2018; Yin, 2018) while well-documented research tasks may support validity (Amankwaa, 2016; Korstjens & Moser, 2018; Lincoln & Guba, 1985). Researchers should follow standard processes and provide in-depth explanations of their activities to establish reliability and replicability of the study (Alase, 2017). Validity may be supported by activities such as saturation (Saunders et al., 2018; van Rijnsoever, 2017; Weller et al., 2018), triangulation (Alase, 2017; Fusch et al., 2018), member-checking (Alase, 2017; Kornbluh, 2015; Lincoln & Guba, 1985; Yin, 2018), extended field time (Creswell & Creswell, 2018; Creswell & Poth, 2018), and thick description (Fusch et al., 2018). For this study, the researcher applied various strategies for validation and reliability and provided extensive documentation regarding these processes with tasks backed by references to the literature.

Transition and Summary of Section 2

Section 2 describes procedures by which this qualitative case study was carried out. Justifications and research theories are provided for each phase of the study. The purpose of the study is reiterated and precedes an exhaustive account of the steps that were taken to ensure research is conducted carefully, ethically, and reliably. To understand how organizations can form a culture of data-driven decision-making, the researcher followed the procedures outlined. The role of the researcher is defined, explaining what positions the researcher must adopt throughout the research process. Participants, as well as the population and sampling methodologies, are described as well. The research methodology and design followed are defined with underlying philosophical assumptions highlighted. Finally, processes for collecting, organizing, and analyzing data are described, as well as the ways in which the researcher conveyed reliability and validity of the ultimate results.

Section 3: Application to Professional Practice and Implications for Change

According to a variety of researchers, decision support tools delivered through technical means can improve the quality of strategic decision-making and ultimately organizational performance (Brynjolfsson & McElheran, 2016; Jabeen et al., 2016; Morton et al., 2018). To benefit from these tools, organizations must first adopt and implement a culture that supports data-driven decision-making (Garcia-Perez, 2018; Halaweh & El Massry, 2015). This qualitative case study seeks to understand the components of such a culture and the ways leaders and change agents can introduce this environment. During the field study, 18 participants were interviewed regarding their experiences with data-driven decision-making in their current job roles. The third and final section of the study provides a detailed presentation of findings, as well as an overview of how these findings can be applied to professional practice. Additionally, specific recommendations for action and further study are provided. Reflections on the study are discussed as well. The study revealed a number of insightful findings related to cultures of data-driven decision-making, including elements of trust in data, the design of data-driven teams, and the processes by which organizations create and defend their culture.

Overview of the Study

This qualitative case study was intended to uncover the forces contributing to and affecting a culture of data-driven decision-making in business. Specifically, the purpose was to investigate the processes by which a medium-sized transportation business works to build a data-driven culture and improve organizational performance. According to researchers, understanding these processes helps inform the creation and maintenance of data-driven strategies (Garcia-Perez, 2018; Halaweh & El Massry, 2015). A qualitative design was employed for the study, with a single case study design. This approach allowed for a deep analysis and understanding of the essence of the experience of undergoing a data-driven culture transformation (Guillen, 2019). The primary topics of interest cover the processes by which a data-driven culture is introduced and how analysts and change agents can persuade decision-makers to rely on facts and insights.

Semi-structured discussions with participants consisted of 17 open-ended questions that each supported one or more of the three primary research questions. These research questions included: (a) what constitutes a data-driven culture, (b) what actions can organizations take to introduce a data-driven culture, and (c) how can business strategists persuade leaders to turn over a degree of decision-making power? These three research questions in turn supported the overall central question addressing how organizations can transform their corporate philosophy into a data-driven culture that supports both productivity and accountability.

While conducting interviews with participants and coding transcripts, various themes emerged that informed the direction of saturation and the eventual recommendations for action. Participants provided analysis of several surprising themes and gave a nearly complete picture of data-driven cultures that can serve to influence future studies. Discussions revealed that participants placed a great amount of importance on trust in data-driven decision support tools. A second theme indicated the necessity of designing and transforming culture, as well as the development of teams. The final theme addressed the design and implementation of work instructions and processes that should be observed in building data-driven cultures and tools. Participant responses provided great insight into each of the three research questions and interactions between these forces.

Anticipated Themes/Perceptions

The review of the literature revealed a great amount of information from prior research. This provided a preview of the themes that would be discovered during the field study. Literature often fell into one of three categories: (a) decision-making in business, (b) business intelligence and data maturity, and (c) culture transformation and characteristics of cultures of data-driven decision-making. Based on these findings and initial perceptions during the field study, it was anticipated that themes would follow this general framework. Participant responses were expected to recommend a model for a data-driven culture transformation, as well as reveal the general characteristics of a data-driven culture.

Various researchers explain that understanding decision-making processes and the ways data interacts with these processes can prove invaluable in building a data-driven culture (Cao, 2017; Gauzelina & Bentza, 2017; Pranjic, 2018; Reymen et al., 2017; Ward et al., 2019). Researchers explain that decisions at even the smallest operational level ultimately drive outcomes at the highest strategic tier of the organization (Mendes et al., 2018; Nikeriasova et al., 2016; Schneckenberg et al., 2017; Weiner et al., 2015). Participants were expected to call attention to this relationship and discuss the need for comprehensive strategies that encompass multiple layers of the business. Furthermore, researchers explain that decision-makers often have difficulty allowing decision support tools to influence their choices and that change agents must persuade leaders to view these technologies as supplements and not replacements (Bogdan & Lungescu, 2018; Cao, 2017; Galbraith, 2014; Grover et al., 2018). Identifying ways to perform persuasive tasks was expected to be a major topic of discussion within the field study.

According to Cech et al. (2018), organizations should work to improve technical and data maturity. Participants were expected to provide an analysis of data maturity and demonstrate ways organizations can improve their own maturity. Many researchers focus on specific data maturity models, with most ranging from immature, disjointed datasets to highly advanced, well-respected decision support models (Al Rashdi & Nair, 2017; Cech et al., 2018; Farah, 2017;

Skyrius et al., 2016; Tavallaei et al., 2015). Several researchers explain that maturity extends to the culture of an organization and not simply technical capabilities (Al Rashdi & Nair, 2017; Gannon-Slater et al., 2017; Mikalef et al., 2018). Based on these revelations, participants were expected to discuss various aspects of data maturity, including technical and non-technical factors.

Cultural transformation was expected to be a major topic of discussion among participants. Akaegbu and Usoro (2017), Argenti (2017), and Gannon-Slater et al. (2017) stated that data scientists and other change agents will be unsuccessful in transforming culture if they are not aware of the key aspects of a culture of data-driven decision-making. Lawler and Joseph (2017) and Mehdi et al. (2017) discussed the necessity of the proper culture and identify this as a prerequisite to becoming truly data-driven. Culture can be supportive or detrimental to organizational goals, though businesses that ensure culture is aligned with goals will often find that their employees are more productive and supportive (Akaegbu & Usoro, 2017; Hassert, 2018; Mehdi et al., 2017; Stacho et al., 2017). Participants were expected to identify components of a data-driven culture and provide a framework for obtaining these qualities. Among many others, researchers showed that a data-driven culture requires technological capabilities and training (Cekuls, 2015; Garcia-Perez, 2018; Halaweh & El Massry, 2015; Mikalef et al., 2018), executive sponsorship (Grubljesic & Jaklic, 2015; Halaweh & El Massry, 2015; Mesaros et al., 2016; Mikalef et al., 2018; Yeoh & Popovic, 2016), fast and public victories (Cech et al., 2018; Grubljesic & Jaklic, 2015), and the implementation of data governance processes (Aragona & De Rosa, 2018; Cech et al., 2018; Farrell, 2018; Lawler & Joseph, 2017; Lewis, 2019). Participants were expected to identify some combination of these components and describe the ways organizations can acquire such capabilities.

Presentation of the Findings

Throughout the data collection and analysis phases, several themes began to clearly emerge. As participants were interviewed and discussions began to achieve triangulation and saturation, a consensus began to be reached among individuals. Although some specific topics were a source of contention, high-level themes were generally agreed upon. Participants in the study identified three major themes, each of which were made up of several more specific components. The first theme that began to emerge related to trust and data maturity. This referred to the ways organizations can create trustworthy decision support tools as well as the ways business intelligence professionals can employ persuasive techniques to encourage the adoption of technologies. A second theme focused on the design of organizational culture and the development and population of teams. This theme comprised the procedures businesses use to define a culture of teamwork, define and populate a cross-functional business intelligence team, and transform the existing culture into one of data-driven decision-making. The third and final theme involved the design of work and the processes organizations should follow when promoting and participating in a culture of data-driven decision-making. These processes included making decisions using decision support tools, setting goals and priorities, managing teams and projects, defining system interactions, adopting data governance procedures, and finding ways to measure success and data maturity. These themes, interactions between themes, and the insights that arise from their analysis inform understandings of the research questions and the components of a culture of data-driven decision-making.

Theme 1: Trust and Data Maturity

One of the most frequently mentioned themes throughout the study was the relationship of trust to data maturity and acceptance of data-driven initiatives. All participants, in some form or another, discussed trust or components thereof. Topics related to trust generally fell into one of two categories: technical buy-in and persuasion. According to participants, technical buy-in refers to the perception of correctness of the analytical end results and consists of six unique dimensions, including (a) accuracy, (b) consistency, (c) availability, (d) actionability, (e) integrity, and (f) completeness. The level of success in these dimensions can be observed, to a degree, in the adoption of such technologies. A second major subtheme identified was persuasion and the tasks necessary to persuade decision-makers to believe in the power of analytical data. Participants stated that although business leaders and other decision-makers can frequently be resistant to change, business intelligence professionals may persuade them to consider data-driven decision-making by (a) socializing projects, (b) engaging with consultants, (c) demonstrating the impact of data-driven technologies on individual workers, (d) issuing propaganda, and (e) allowing the data to prove itself. Finally, these subthemes are correlated to teamwork and team management, a key focus of Theme 2.

Subtheme: Buy-in and Technological Trust. A crucial component of trust and growing data maturity, according to participants, is the ability to rely on data for making the right decisions. This form of trust relates to the technological relationship a decision-maker builds with his or her data. This is highly consistent with the assertions of Garcia-Perez (2018), who stated that trust is crucial to instituting a fact-based culture, using adoption of technologies as an intermediary. According to Cech et al. (2018) and Grubljesic and Jaklic (2015), this form of trust can be obtained through key victories. Of the 18 participants that took part in the research, 16, or 89%, stated that *trust in data* was a critical component of a data-driven culture. Many implied that trust in data can act as a proxy to measure the extent to which an organization is data-driven. Participant 14 claimed that trust is a prerequisite for being data-driven:

> Because right now, it's not accurate, that kind of drives them away from trusting it. So, that's one thing we need to make sure of, that we gain the trust of our users, before we can be a completely data-driven company.

Though trust, as discovered through conversations with participants, is highly multi-faceted, many employees spoke generally about the relationship between trust in technological solutions and the ability to become data-driven. Participant 11 similarly referred to this phenomenon as having confidence in technological solutions:

> And that's kind of where we struggle, and then you end up with people that don't have much confidence in the data. If it's not implemented correctly, you can undermine your ability to move toward a data-driven culture.

According to some participants, technological trust is key for decision-makers to confidently make decisions. Participant 5, for example, discussed the role of technical buy-in with regard to improving data maturity and trust in decisions:

> We had a data-driven culture, and we were actually transitioning, and we had buy-in from everyone, and the more buy-in we got, the more mature we got, the more they trusted their decisions.

Analytics team members such as information technology personnel and analysts within the organization should strive to identify and remove barriers to trust in data. According to Participant 9, removing such barriers improves relationships between decision-makers and data:

> They don't have so many people going around asking questions, they just go with it. They don't have to spend the entire day worrying about if the data is correct, they can do their own thing and work on things they really need to be working on.

Trust in data can often be related to *adoption of technologies*. Garcia-Perez (2018) noted that trust leads to adoption. Bogdan and Lungescu (2018) explained that insights are of no use unless adopted by key individuals. Achieving adoption of technologies, particularly business intelligence solutions, is of significant difficulty and can be considered a competitive advantage (Halaweh & El Massry, 2015). Three participants, or 17%, noted that adoption of technologies is an important factor in determining trust. Participant 12 stated that ensuring solutions are accepted by business users is a key component of success in business analytics:

> I think change management is a huge thing for most companies. I think that’s probably what contributes a lot to some companies’ successes or failures. How the personnel is either managing the data or using the end piece of software, how they accept it.

According to participants, data trustworthiness comprises six dimensions, including (a) accuracy, (b) consistency, (c) availability, (d) actionability, (e) integrity, and (f) robustness and completeness. All participants discussed at-least one of these dimensions. The first of these dimensions, *accuracy of data*, refers to the closeness to which the nominal values provided by the data resemble the business user’s perception of truth. Researchers often explain that data-driven cultures can contribute to the accuracy of an organization’s data outputs, often elaborating that such a culture allows data scientists to have the freedom to participate in activities that contribute to greater data accuracy (Bogdan & Lungescu, 2018; Cech et al., 2018; Halaweh & El Massry, 2015; Mikalef et al., 2018). Such activities can provide data scientists with the ability to adapt to changes in the environment and business processes, leading to enhanced accuracy (Villamarin-Garcia & Diaz-Pinzon, 2017). Participants overwhelmingly affirmed the relationship of data accuracy and data-driven cultures, with 16 of 18 participants, or 89%, calling attention to the phenomenon. Participant 14 demonstrated the importance of data accuracy to proper decision-making:

> Well, the accuracy of your data… if it's not accurate, then you're not making the right decisions for your company. If… I really believe that would be the driving force of what it is. The accuracy, data quality.

Inaccurate data can result in incorrect decisions on behalf of the organization. Data presented to business owners must be accurate to provide the most useful information. Participant 11 explained that recommendations provided to decision-makers must be backed by accurate data: "I'm going to go back to accuracy and consistency in the data. You need to be able to show them empirical information, almost irrefutable."

Accuracy in data is a significant contributor to trust in data. This trust, according to participants, is built over time and is the result of constant, reliable accuracy in analytics. Participant 6 called attention to the need for long-running accuracy in reporting:

> They look at the data and they believe the data, you know, because they can trust it, because it's always been accurate. […] It's like building up trust, you've got to have it in place and you've got to have it working good for a while for people to really trust it and stop questioning it.

As an essential part of trust in data, accuracy should, according to participants, be a common goal between business intelligence solutions. Data scientists and analysts should strive to achieve an acceptable degree of accuracy and maintain this level of service over time. Preserving the correctness of data over a prolonged period of time contributes to a stronger, more trusting culture that reciprocally helps improve the accuracy of the data (Bogdan & Lungescu, 2018; Cech et al., 2018; Halaweh & El Massry, 2015; Mikalef et al., 2018).

The second dimension of trust in data, *consistency of data*, refers to the extent to which analyses match with previous reporting. Farrell (2018) and Lewis (2019) explained that data consistency is necessary for creating a data-driven culture. Of the 18 participants interviewed, 11, or 61%, reported the importance of data consistency. Participants noted a distinction between the concepts of accuracy and consistency, explaining that organizational users may differ in their definitions of a particular metric. These often-subtle differences result in two equally accurate but inconsistent metrics. Participants noted this as a particular problem in their own organization, explaining that having frequent inconsistencies erodes trust in data. Keeping results consistent, or properly labelled, contributes to the overall trust in an organization's data. Participant 11 noted the difference between accuracy and consistency and asserted that consistency is a larger factor of trust than accuracy: "I mean, accuracy of data, and I wouldn't just say the accuracy of it, but if it's consistent. Maybe accuracy is a component of that, but consistency is the main thing."

Building analytical solutions that are consistent with prior deliverables builds trust over time; delivering solutions that are accurate but full of inconsistencies can inhibit trust. Participant 1 confirmed by asserting that trust can be diminished over poor consistency of data: "Be very consistent, because as soon as you see two different reports reporting the same thing, but they are different numbers, that's where that trust gets degraded."

Several participants noted specific effects of both highly consistent and highly inconsistent data environments. Participant 18 explained that when data are presented consistently in the same format and labelled correctly, users indicate a willingness to utilize data: "And every data point has its own nomenclature, so if somebody pulls data and somebody else pulls similar data… guess what? It's the same data. We're not going to pull different solutions just because…"

When data are inconsistent, trust is weak. Participant 7 noted that a single instance of inconsistent data can result in loss of productivity: “That’s a huge step in the right direction, because instead of spending all your time arguing about why data is the way it is on one report, and why is it different on this other report…”

Understanding the role of consistency as a factor of trust is important to its maintenance. Participants clearly believed that trust and data were undermined when reporting was poorly presented or inconsistent with what they understood to be definitions driving analytics. According to participants, analysts should maintain a high degree of consistency with regard to data insights and presentation.

As the third component of data trustworthiness, *availability of data* refers to the ability of decision-makers to access insights, both from a security standpoint and the perspective of system up-time. This may also comprise the timeliness and stability of systems. Gioti et al. (2018) addressed availability of data, imploring organizations to consider if any analyses should be restricted from the organization at-large. Cech et al. (2018) further explained that although availability of data contributes to trust in systems, this relationship may be two-way; data-driven cultures often determine the ability of analysts to access data for use in future insights. Participants frequently referred to data availability as an important component of trust, with 12 of 18, or 67%, calling out the relationship. Participant 15 succinctly stated that “people are more likely to use a product if it is easily accessible.” Participant 3 divided accessibility into several components, stating: “I think that they need to make sure that the reports they are writing are accurate, stable, not poorly performing, highly available, communicate changes.”

Participants clearly conveyed the idea that data must be available for consumption for organizations to become data-driven. Several participants noted that availability can include the ease with which data consumers can process data. Participant 4 demonstrated the need for tools allowing for mass consumption of datasets: "[If you] don't have good tools in order to analyze large datasets, it's going to be slow and inefficient and they're going to get frustrated and they're just not going to want to do it."

Some participants explained that data can have a useful lifespan, indicating that quick access to data is needed to maximize the impact of being data-driven. Participant 8 explained that databases and analytical tools must return insights quickly to maintain high availability of data:

> We dealt with a couple different systems where, if you would do a search or a query, it would take… latency on the request would take so long […] that you could actually make a decision on your own as a human being instead of allowing the computer to return the information to you.

Ensuring data are accessible, systems are stable, and solutions are timely are activities participants claim are crucial to building an environment that trusts data and adopts a data-driven culture. By demonstrating the highly accessible and stable nature of systems, researchers and data scientists can begin to win trust from system users who expect consistent availability of data.

The fourth factor of trust in data, *actionability of data*, suggests that data must have a practical use for decision-makers before it becomes trustworthy. This also indicates that analytical solutions should be concise and refrain from presenting unnecessary complexity. Researchers frequently find that actionable insights lead to productivity and profitability within a business (Arghir et al., 2019; Bajari et al., 2019; Nykanen et al., 2016; Popovic et al., 2018). Skyrius et al. (2016) and Villamarin-Garcia and Diaz-Pinzon (2017) explained that the culture of an organization can impact adaptability and that this adaptability drives usefulness of insights.

As a contributor to the overall trust in an organization's data, its actionability is a stepping-stone in the business analytics maturity curve (Mikalef et al., 2018). A significant number of participants, six of 18 (33%), noted that data must be actionable to drive its trustworthiness. Participant 2 concisely stated, "I think you need data that is actionable." Participant 1 defined actionability in terms of the usefulness of analytics: "I think individuals need to know what that number means, then know what the lead measures are that impact that number."

By understanding what metrics and insights are being measured, and being able to identify lead, contributing factors, decision-makers can take specific actions to maintain course or make adjustments to the way business is conducted within their circle of influence. These abilities contribute to decision-makers' overall trust in data solutions. Participants also called out the importance of restricting operator visibility into non-urgent, unimportant analyses. Participant 10 specifically called out the difficulty of decision-makers in processing unrestricted and unruly amounts of data:

> We've got some employees that… they want to see everything, and from my experience, your average person can only absorb and use a certain amount of data, and if you put too much in front of them it actually… I don't know whether it confuses the individuals or if it is so much they miss things.

Analysts and data scientists should work to ensure that the information being provided to business decision-makers is succinct and that information being provided is necessary to make the desired decisions. Finally, participants often agreed that the possession of a data-driven culture and increased reliance on data for actionable decision-making provide additional capabilities that improve an organization's data maturity. Participant 8 stated that maturity comes with the ability to answer decisions based on the data provided: “The next level [of data maturity] would be when you start to mine that data and start making decisions based off it.” Becoming data-mature is the ultimate goal of individuals aiming to create a data-driven culture. Instilling trust in decision-makers is a logical step in this process participants frequently called out. Actionability and the degree to which data encourages decision-making is a significant factor in gaining trust.

Many participants referred to the *integrity of data*, the fifth aspect of data trustworthiness, distinguishing this from the accuracy of data. Whereas accuracy is concerned with the transformation, analysis, and presentation of data, integrity focuses on the collection and storage of information. This ensures that data stored in a database is reflective of what system users or sensors input into source systems, as well as its incorruptibility once it is stored in a repository. This is reminiscent of the statements of Bajari et al. (2019), who claimed that business intelligence solutions are most effective when organizations improve data collection processes and storage mechanisms. Among the 18 participants in this study, 12, or 67%, mentioned data integrity as an important source of trust in the organization’s data. Several participants alluded to data entry processes and their importance in maintaining consistent data collection and formatting. Participant 4 stated the relevance of data integrity to the quality of output: “If that process is not broken and it’s a good process, and it’s being stored correctly, and it’s being pulled correctly from whatever application is pulling it… if all those things are correct, then output is fact.”

Developing and maintaining processes to govern data entry is a component of maintaining trust in data. Executing these processes and holding system users accountable to the accuracy of data is important as well. Participant 2 discussed the necessity of overseeing these processes: “I think if you’re holding people accountable, it is a lot easier to get clean data and make people be more consistent in how they’re inputting data in the system.”

Data maturity, trust, and data integrity are strongly linked, according to participants. Several participants discussed the ties between culture and the maturity of an organization, demonstrating the importance of quality on the front-end to data accuracy on the back-end. Participant 10 stated that culture impacts data integrity:

> You’ve got to have, to me, to drive the maturity, the culture on the front-end, otherwise it becomes garbage in, garbage out. If you have the culture on the front-end, I think you drive the accuracy of the inputs, which will enable you to mature your data over time.

Similarly, Participant 12 explored the relationship of front-end inputs to back-end outputs, also describing that culture should in some ways target these inputs:

> I would say one that places a high value on the data integrity inputs itself. You know, obviously, the better the data that you input, the better results you get on the outside. And I think placing a heavy emphasis on it, you’re liable to get better and more optimal results on the back-end.

As a component of trust, regulating the integrity of data in the system requires buy-in and participation from all areas of the organization; this is an early demonstration of the wide scope of data-driven cultures. Although analysts and data scientists can encourage and, in some cases, enforce data entry procedures, data-driven cultures are influenced, either positively or negatively, in some way by all members of the organization.

The sixth and final component of trust in data, *robustness* or *completeness of data*, refers to the volume and breadth of analytical systems. Several participants noted the expanse of data, explaining that insights and analyses must be reasonably wide in scope; systems that have very narrow and specific use cases do not always foster a sense of trust in medium-sized organizations. Solutions, participants stated, must involve a large portion of the business; this foreshadowed their beliefs concerning the expanse of culture over an enterprise. Barua and Mondal (2019) explained that this can sometimes create technical challenges for organizations and lead to increased spending in information technology areas. Bajari et al. (2019) showed that large datasets traditionally improve performance of the overall organization, but caution that overly large databases can reach a point of diminishing returns or create more problems than they solve. Nevertheless, four of 18 participants, or 22%, stated that datasets should be large and span the full organization. Participant 8 connected the scope of data gathering to the scope of a company's culture, indicating that data-driven initiatives should be executed company-wide: "You can't just grab data from one aspect of the business. If you want to truly be a data-driven company, you've got to grab data from all aspects of the company."

As datasets grow and information is consistently collected over a long period of time, analysts may use large volumes of data to demonstrate trends and use past data to predict or drive future behavior. Participant 11 stated that historical data can help understand potential future scenarios and guide decision-makers toward or away from particular choices:

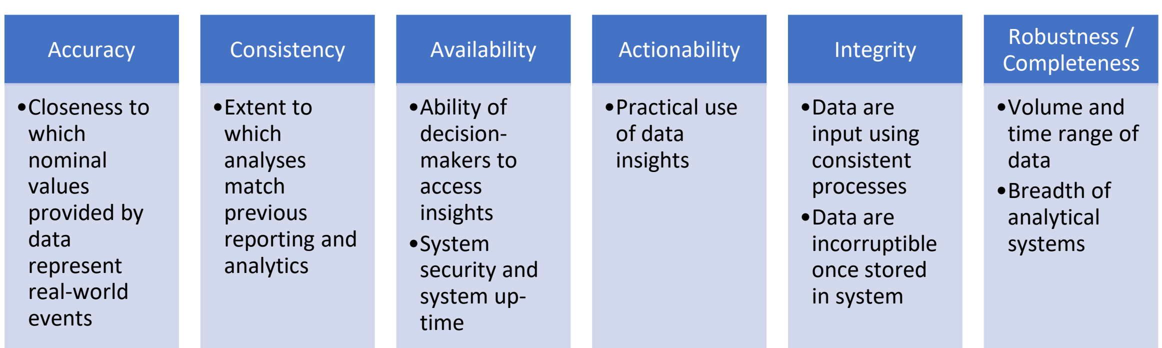
> If your company is a data-driven culture, the fact that you're collecting all that information and using it to make your business decisions, the more data you collect over time, helps you to understand maybe trends in the business and the marketplace, helps you to avoid some issues because you have history, you've seen this before.

Analysts and data providers should be careful to balance the need for robust datasets with the need to maintain actionability of information. Finding the appropriate balance in each dataset is a crucial component of creating a sense of trust between decision-makers and data.

Data scientists and analysts should be careful to adhere as much as possible to the six dimensions of data trustworthiness. Ensuring the accuracy and consistency of data is critical to providing valid analyses over time. Being careful to maintain the availability of systems allows decision-makers to know that data are accessible when or before it is needed. Analysts who provide actionable data convey to decision-makers that they understand the organization and what data points are necessary to make rational, informed decisions. Engaging with operators within the organization can improve the integrity of data entered and stored in technology systems. Finally, robust and complete datasets can ensure that decision-makers have all relevant data necessary to make good decisions. Participants collectively showed that these six qualities of data are what largely improves trust with organizational decision-makers. Figure 3 outlines the relationships between qualities of data and trust from business decision-makers.

Figure 3

Six Dimensions of Technological Trust



As it relates to technological trust in data, *user involvement* refers to processes by which analysts and data scientists work with decision-makers to develop analytical solutions. Such engagements often include defining requirements, understanding end goals, regular check-ins, and validation phases, foreshadowing participant beliefs concerning data governance processes.

Researchers frequently contend that conducting these processes closely with ultimate decision-makers can earn trust for business intelligence teams (Grubljesic & Jaklic, 2015; Skyrius et al., 2016). Although this may require additional soft skills, working directly with end users is a useful way to demonstrate several of the six aforementioned dimensions of trust (Yeoh & Popovic, 2016). Of the 18 participants in the research study, 11 (or 61%) discussed the need for user involvement in analytical development processes. According to Participant 6, business intelligence teams should partner with decision-makers to help provide a deeper understanding of data processes and instill trust in analyses:

> I think the only way you're going to get them to do that is to have them heavily involved and make them a partner in the development of that data and over time too, where the data comes from, how we compiled it, how we're displaying it.

This close working relationship with the ultimate users of systems allows users to become intimately familiar with qualities of data that correspond to one or more of the six dimensions of trust. In corroboration, Participant 16 made a poignant cultural reference demonstrating that decision-makers that are heavily involved in developing analyses are often likely to derive value from the resulting outputs:

> I think they have to be involved in the use cases up front. I'm a big believer in "if you get people to help you build it, they will come." […] It's the *Field of Dreams* theory. They've got to help build the field, and then they'll want to play on it. They help you build your dataset and they're helping you build the use cases and they're helping you validate them.

Data analysts and those responsible for business intelligence solutions should work with end users throughout the development of systems to help foster a sense of trust in data solutions. This relationship can also help expose potential deficiencies in one or more of the six dimensions of trust so that such gaps can be addressed.

To obtain technical buy-in from target audiences, data analysts should work to provide outputs that are themselves trustworthy. Trust in data systems can frequently be measured by the adoption of systems. This trust takes the form of six primary dimensions, including (a) accuracy, (b) consistency, (c) availability, (d) actionability, (e) integrity, and (f) robustness and completeness. Partnering with users throughout development processes, where possible, can help identify gaps in trust and can improve decision-makers' trust in one or more of these dimensions. Trust in data, as defined by participants, is an important component of data maturity and creating a data-driven culture. Additional supporting statements corresponding to the themes of buy-in and technological trust can be viewed in Table 1.

Table 1

Identified Themes and Supporting Statements – Buy-in and Technological Trust

Identified Theme	Supporting Statements
Trust in data	"I think that where they need to start is, write accurate reporting and trusting that reporting and utilizing it to make those long-term decisions, and trusting the data to do that."
	"Obviously your [Financial Planners and Analysts], and people behind the data are going to buy in to the data that they're giving and how they think it's important, but having the operational people and the people that don't think analytically, getting them to buy in is huge."
	"First of all, the data's got to be trustworthy."
	"I think as long as the information it is generating is accurate, your team is going to follow it. But the minute they can poke holes in it constantly, then they have no… you're not going to motivate them to trust the data and improve from it."

	"You've got to get your users to trust the tools and the data that you're providing to them, and until that can happen, you're not going to get far."
Adoption of technologies	"I see going forward that companies that embrace IT are going to be so much further ahead when it comes to data. I mean, it's not like it was when I was going to school in the 80s and 90s when you could pull up a spreadsheet and dump some information in there and you look like a hero because you gathered data. […] You have to embrace IT a little bit more."
	"Adoption of the products, you could look at usage to ensure that it is being utilized by all the different departments."
Accuracy of data	"You need to make sure that the data is accurate so it can't be contested."
	"I think that where they need to start is, write accurate reporting and trusting that reporting and utilizing it to make those long-term decisions, and trusting the data to do that."
	"The data has to be correct, but that has to be vetted out in the way that you look at the data and the way that you clean the data to make a determination on whatever it might be, whether it's a driver or a truck or a piece of equipment of some type, as to how you make decisions about that data."
	"To me, maturity is accuracy, depth, and the ability to actually do more with it."
	"I think it's just going to be in the accuracy and understanding the logic that is behind the reporting. As long as they understand what the logic is, and they believe in the accuracy, then I think it's there."
	"It drives data quality in that the data is of good quality in terms of accuracy and timeliness."
	"Bad data, and the inability to recognize bad data, because you kind of have to gut check yourself sometimes."
Consistency of data	"If you have one set of data and they're used to looking at another and it doesn't match, it creates a barrier and people don't really trust the report or accountability measure."
	"Maybe having one source of whatever it may be, but one source in the tree as opposed to maybe trying to achieve, or retrieve sources of data from several different systems."

	"The problem with all that is, we're now giving people a bunch of different ways and people don't really know what's the best way, because too often if we have reports that are going down a different road, you have reports that don't have the same data, not reporting the same way."
	"We've got a little bit of a history here where you can pull three different reports […] and get three different answers."
	"I think everyone's singing from the same sheet of music. If everyone's using the same data points and kind of having one truth to operate from, it allows every unit of the business to make decisions without having a negative impact on the other. So, it just allows kind of a cohesiveness throughout the organization."
	"Maybe something that genuinely reports the numbers right, and this sounds terrible to say, but doesn't have contradictions."
Availability of data	"If they're not currently data-driven, they're going to have to make sure they have the data available."
	"Data at the fingertips of the user to where they can make informed decisions based on the data."
	"It drives data quality in that the data is of good quality in terms of who can slice it and dice it."
	"Our organization does not have access to go pull data. So, I think it's made us slow, we rely on a few points of… I should say, a few capable people to build views the way we want."
Actionability of data	"I think if you can somehow condense that information into actionable intelligence, then it allows them to do their jobs."
Integrity of data	"I think the very first thing is to have data integrity."
	"If you have a process that's the same for everyone, and everyone's entering it the same way, and you have one neutral source that it's being fed into and being pulled out of, and distributed amongst your applications, that kind of eliminates the debate of whether or not the data is correct […] 'You're the one following the process and entering in and it's going here and coming out of the same system, so, garbage in, garbage out,' I guess you would say."
	"In order to have a good, data-driven culture, you have to have good data."

	"The main risk is the data being incorrect, but hopefully that doesn't happen. But that's always a risk that the measures or the way things were done was just the wrong data, the wrong way to look at it."
	"We need to make sure that our data is clean."
	"One would be data quality. If the data quality isn't there, then I think people are less likely to believe it."
Robustness and completeness of data	"… they have governance over, and execution over their plans and people and make their decisions based off the data, and ensure that all points get covered and they don't miss any points in between because they may have failure to fully get competency in that process…"
	"We have to create the environment with the data, then you need to make sure people… if you can make the data easily accessible, even just basic stuff. And I guess it's just got to be collected and made available in a way that we're capturing everything."
User involvement	"They'll believe in the data and they've got to believe in the data […] but in order to get them to use the data and let the data drive them, perhaps in a way that they probably wouldn't, […] they've got to be part of putting it together in order to believe it. They've got to be part of it."

Subtheme: Persuasion. In many cases, obtaining buy-in from the technical perspective is not enough to foster a sense of overall trust in usefulness of data in decision-making. Participants frequently referred to the need for business intelligence teams to use soft skills to persuade decision-makers to subscribe to the idea of data-driven decision-making, noting that confidence in analytical correctness is not equivalent to data maturity. Researchers overwhelmingly show that instituting a culture of data-driven decision-making requires the trust of key decision-makers (Grubljesic & Jaklic, 2015; Halaweh & El Massry, 2015; Mesaros et al., 2016; Mikalef et al., 2018; Yeoh & Popovic, 2016). Despite believing that data insights are correct, many decision-makers often fail to see its usefulness and are *resistant to change*. This is a unique challenge brought by the relatively new emergence of business intelligence technologies, as well as the perceived threat to decision-makers' autonomy. A significant number of business managers remain hesitant to adopt analytical technologies and must be persuaded beyond simply demonstrating technological correctness (Bogdan & Lungescu, 2018). Three participants of the 18 in the study, or 17%, discussed this phenomenon, agreeing that humans are generally resistant to change. Participant 6 addressed meeting resistance, stating: "They'll always question… anything changes, people don't like change. Because they don't trust change."

In some cases, resistance to change affects not only adoption of technologies but the ability of analysts to provide quality work. Participant 12 discussed the possibility that analysts gathering information could encounter resistance that can make the task of developing decision-making tools more difficult:

> I would definitely go to the end users, because they're probably going to give you the most… some input out of fear, because their concern is going to be what you're going to do to make their life harder… but you'll also get some raw info too.

Decision-makers that display a resistance to adoption of data-driven technologies must be persuaded, separate from practical means, to trust and utilize the power of the available technology.

Throughout data-driven initiatives, business intelligence teams should strive to *socialize projects* throughout the organization. This socialization allows teams to inform skeptics and others throughout the organization of the benefits of adopting a data-driven culture. Communicating with decision-makers and winning trust through socialization requires effective soft skills (Foster et al., 2015). Being able to discuss projects with others is one of the various skills participants identified as necessary for individuals working on analytical endeavors. Garcia-Perez (2018) noted that analysts must understand data processes and use cases to effectively socialize it is worth throughout the organization. Of the 18 participants in the study, four, or 22%, mentioned socialization as a critical step in building trust throughout the business. Participant 15 discussed the importance of the widespread discussion of projects, focusing especially on the ways that such initiatives can improve the organization and the ability of decision-makers to make effective choices: "I think what they have to do is communicate and socialize the project around the organization at every level, and explain the importance that it's going to have on the organization and on the end user."

When discussing potential or current projects with others in the organization, analysts and data scientists should promote the benefits of such work. Participant 10 explained that a major component of socialization is helping potential users understand how new processes and systems can positively impact their specific area of the business:

> You've got to teach them what is in it for them, because that's how human beings work. So, when you teach them and you make it very apparent to them what is in it for them or for their team or for the overall organization, the open-mindedness and willingness to become part of being a data-driven culture comes much easier.

Participants showed that building rapport with targeted individuals can be a useful way to socialize projects and gain trust in the organization. This exercise helps decision-makers begin to understand the definition and goals of projects in an effort to earn additional trust throughout the transformation process.

Several participants called out the potential need to *involve consultants* in data-driven initiatives. This involves consultants in terms of both project management and technological resources. Yeoh and Popovic (2016) corroborated these assertions, explaining that business intelligence teams should include an experienced external consultant that can provide guidance and help organizations gain trust. Although consultants can bring notable contributions to the projects themselves, they also possess the unique ability to instill confidence throughout the organization in ways that internal employees cannot. Participants distinguished business consultants from IT consultants, with three of 18 participants, or 17%, discussing the importance of gaining outside perspective when implementing data-driven initiatives. Participant 13 explained the need for outside consultants, elaborating that consultants bring a fresh perspective that cannot adequately be sourced from internal employees: “Sometimes, we are so close to it that maybe we overlook or just don’t see something that can be done a different way or a better way. Sometimes, it’s probably good to bring outside in.”

Fresh perspectives can help businesses overcome missteps and biases held by individuals that are part of the organization. Consultants can provide the unbiased view of the organization and its data without getting embroiled in organizational politics. Participant 3 discussed the ways third-party consultants can provide a unique perspective that internal employees cannot provide:

> The internal team… they’re going to know the business. They’re going to know how to start getting that data out there. That third-party may be an in-between where they have an unbiased opinion toward the data or how it should be represented. Maybe they don’t have a stake in the company like the analysts do, where the analysts could be persuaded to make the numbers look better, versus the third-party being that divider.

Many participants explained that technology consultants can be a helpful way to instill trust as well. These consultants often bring a degree of credibility that individuals within the organization do not possess. Despite internal employees sometimes possessing the technical capabilities necessary to implement data-driven systems, participants explain that external consultants have additional resources and authority that internal resources cannot provide. Nine participants, or 50%, discussed the usefulness of external technical consultants. Participant 4 explained that companies may be forced to use consultants due to a lack of competencies within the organization and the inability to, especially in medium-sized organizations, to attract top talent for internal positions:

> I think it depends on the resources of your company. If the company has the resources to handle that all internally that's really the best recommendation, because they're familiar with that company and know what's going on. And if they don't, it's probably best to get somebody from the outside to teach them how to do that.

In some cases, despite organizational capabilities, businesses may enter into agreements with contractors to expand capacity or leverage a consultant's credibility to drive adoption and trust in a system. Participant 16, for example, discussed the possibilities of using external resources to achieve goals:

> I do think it's helpful to have a partnership outside, an external partnership, that helps facilitate […] I'll be the first to say, consultants always have better street cred than your internal experts, so use their credibility until they prove that they don't have any, and their facilitation skills, to help with their strategy and prioritize what you want.

Using external consultants to gain confidence can be a useful way to build trust within the organization. Identifying gaps in capabilities and trust can help organizations understand if consultants are necessary, as well as what competencies the right consultant would need to possess. Whether business consultants tasked with providing an unbiased look at organizational data or technological consultants trusted with building technical solutions, outside contractors can bring a level of trust to an organization's data that internal resources are unable to provide.

Data analysts and leaders of data-driven initiatives can help earn the trust of individuals by demonstrating what such projects can do for people. Providing tools that help decision-makers make better choices, or eliminate the need for performing tedious tasks, can help build trust. Importantly, however, business intelligence professionals must demonstrate these benefits to decision-makers using soft skills and persuasion, not simply technical accuracy. Researchers frequently explain that data maturity is positively affected when strategic decision-makers understand the ways technical solutions can improve organizational metrics (Al Rashdi & Nair, 2017; Cech et al., 2018; Farah, 2017; Skyrius et al., 2016; Tavallaei et al., 2015). Participants argued that guiding users to understanding *individual impact* satisfies this requirement and improves trust in data-driven initiatives. Four of 18 participants, or 22%, made this assertion, explaining that engaging with users to demonstrate individual impact helps the quality of work and adoption of technologies. Participant 10 spoke on the ways business intelligence teams can communicate with individuals to help them understand how the inputs they are responsible for can improve the quality of outputs:

> It’s got to be real-world application for them, so, I think it starts with education on what’s going to occur with the data, and you’ve got to educate on where the data is coming from, and help them understand how the actions that they take… you know, it starts with them.

On the back-end, analysts can persuade decision-makers to make use of outputs by showing individuals what benefits they can receive by participating and adopting technologies. Participant 16 explained that potential users must be shown what advantages they can obtain by implementing data-driven solutions:

> Plus, there’s got to be a win in it for them, and I go back to the quick wins thing. It always comes down to, “What’s in it for me? Are you going to make my job easier? Are

> you going to help me make better decisions? Provide me data insights that I didn’t have before?” That’s going to be key in order for them to jump on board.

Explaining to decision-makers the ways in which they can contribute to a data-driven culture and what benefits they can personally receive helps drive adoption and trust in new technologies. Organizations can gauge their success in these demonstrations by evaluating the degree to which employees understand their place in the business. Participant 2 mentioned that employees should know how their decisions affect the overall business: “If you can make it where everyone can understand and see the overall impact of a decision they make, that’s when you know you’ve changed your culture.”

Showing individuals how they can impact and benefit from a data-driven culture helps persuade employees to establish rapport and trust with business analysts. Engaging with users to begin or develop these relationships can help analysts provide better outputs and drive, from the strategic level, adoption of data-driven technologies.

Some participants called out the use of *propaganda* as a useful tool in achieving trust throughout an organization. This involves using tactics such as town halls, email communication, and demonstrations of success to keep data-driven initiatives in front of business users. Foster et al. (2015) explained that early successes in technological solutions can help show skeptics that business intelligence has use within the organization. This display can be achieved through internal marketing (Foster et al., 2015). Demonstration of data-driven project successes should be performed by leaders in the organization, wherever possible (Mikalef et al., 2018). Several researchers note that data maturity models frequently ignore internal marketing needs in data-driven initiatives, showing that this is often an overlooked part of the process (Bogdan & Lungescu, 2018; Chen & Nath, 2018). A small but significant number of participants (three of

18, or 17%) noted the need to use propaganda in gaining organizational trust for data-driven decision-making solutions. Participant 3 discussed the need to implement propaganda campaigns during the initial establishment of a data-driven culture: “Most of them will do some type of propaganda. They’ll put those values directly out in front of you through different mediums, whether it be through email, weekly emails discussing the values, department meetings through your manager.”

The use of propaganda is not limited to gaining initial trust with organizational decision-makers. As time progresses, the novelty of data-driven initiatives erodes, and executives move on to other priorities in the organization, business intelligence teams can continue using propaganda to maintain the hard-fought culture. Participant 10 discussed making benefits of data-driven projects visible throughout the organization: “You have to celebrate the wins. The benefit of the projects that come out of a data-driven culture have to be visible to everybody.” Business executives may, after implementation of a data-driven initiative, hope to reallocate resources away from business intelligence teams. In extreme cases, they may want to abandon projects altogether, forgetting their benefits. In these cases, analysts and those hoping to preserve a data-driven culture must defend its necessity. Participant 8 explained that analytics teams must frequently remind leaders and decision-makers of their value: “You’ve got to reeducate and reidentify what the numbers of it are and show it in a manner that prevents them from denying the system.” Communicating positive effects of data-driven initiatives throughout the company helps increase trust in technologies. Propaganda can be a highly effective tool when working to persuade decision-makers to make use of data-driven decision-making tools.

Participants were asked to describe ways that business analysts could persuade decision-makers to use data-driven tools in place of feelings when making choices. Responses strongly suggested that data, if accurate, can prove its own worth. Researchers support this claim as well, stating that correct data generates trust in data-driven initiatives and that analysts hoping to sway decision-makers a particular direction can use data to do so (Bogdan & Lungescu, 2018; Cech et al., 2018; Halaweh & El Massry, 2015; Mikalef et al., 2018). Of the 18 participants in the study, 13 (72%) stated that *data can prove itself*. Two participants who serve as leaders in the organization explained that data, as a representation of factual information, can be used to persuade them to change decisions. Participant 15 asserted that demonstrating a decision is wrong through data is the most effective way to change a choice: “I think a lot of times as business leaders we have a tendency to go with our gut, so really just providing facts and cold hard truth is the best way to persuade someone to go a different direction.”

Similarly, Participant 18 explained that analysts who identify and provide insight into problems carry weight in the organization, going further to suggest that analysts should bring solutions to these problems:

> Any analyst that can bring good data with a conclusion, or even a theory or some step further, a suggestion on what to do about it… I’ve always listened to that. I find it to be… they’re more influential than other people.

Several participants provided additional detail concerning ways to model data and present to decision-makers. Some participants noted that some leaders are highly adept to raw data and statistics while others must have data presented visually to appreciate the value of the information being provided. Participant 13, a leader in the organization, affirmed this belief, stating that analysts wanting to affect decisions should prepare visualizations:

> I'm very visual. If someone can show me that there's a better way or 'this is what the information says,' and I believe that information, then I'm going to be open. But if I don't have that information in front of me, it's very hard for me to get on the bandwagon.

Participant 14 discussed successfully contributing to decisions by supplying leaders with visual representations of data:

> Provide reports and reporting data behind the report. I guess the report can include graphs and charts that will allow them to actually see […] how our company is performing and growing. So, providing reports and also the data behind it.

Well-designed visualizations provide a quick way for leaders and decision-makers to understand a complete picture of the state of the particular entity being measured. Several participants identified a highly effective but difficult-to-produce method of persuasion, explaining that analysts can create predictions using historical data to forecast future results. In some cases, such forecasts can take time and require a degree of technical and mathematical skills, indicating that researchers must be diligent and highly explanatory when employing this method of persuasion. Participant 7 explained ways analysts can use the predictive methodology:

> That's the most effective way to prove stuff, is to have an outcome that no one knew beforehand or maybe they could have avoided, and the data is proving itself with the results, if the results are accurate with what the analytics said.

Participant 8 delved deeper into this example, explaining that analysts can use partitions of past data to complete predictive models to complete analyses with greater speed and communicate with leaders faster:

> Predictive models don't just apply to recruiting, or to safety, or collisions, I think they apply to everything. And so, if you could sit down with individuals and say, 'Look, I

> don't know what happened in the past. I'm going to put a predictive model together and show you what happened six months ago, or a year ago, or two years ago, based on the data.' And begin with that type of modelling where you can show them that the information that you're going to give them, the decision-making that you're going to have the ability to use the data for, is truly correct.

Participants stated that allowing data to prove itself creates momentum in the organization with regard to data-driven cultures. Participant 4 explained that leaders are more likely to invest in business intelligence teams if data proves accurate and analysts can persuade users to adopt technologies through data correctness:

> By relying on this data, by doing this analysis and taking this data and using it to become more efficient and be able to cut out waste and generate more revenue, more productivity, and also generating more profit… that right there is one way for leaders to say, 'Well, there's something to this, we want to do more of it.'

Allowing data to prove itself, supplemented by analysts making an effort to present data according to the preferences of individual users, is a useful way to persuade decision-makers to adopt data-driven technologies.

A major component of trust and data maturity, as identified by participants, is persuasion. Despite the potential technical accuracy and trust decision-makers place in technical solutions, leaders and operators frequently require additional persuasion that can be provided only by a human. Through (a) socialization of projects, (b) use of consultants, (c) demonstrating positive impacts to end users, (d) propaganda, and (e) allowing data to prove itself through proper methodologies, data analysts and business intelligence professionals can improve trust in decision-making tools throughout the organization. Further supporting quotes from participants regarding the theme of persuasion are provided in Table 2.

Table 2

Identified Themes and Supporting Statements – Persuasion

Identified Theme	Supporting Statements
Resistance to change	"You're going to have people that have their own processes and you're not going to change it."
Socialize projects	"I think it goes back to 'here's some of our hurdles, here's some things we can do to improve it,' so they can see progress, or see the improvement."
Use of consultants	"Externally, there may be a resource to help you compile that data into something that's useful, maybe as a third-party person that are looking at it from the outside in to give you an unbiased approach."
	"You've got to be able to work with the third parties in order to have them compile the data that you need, then be able to give it to you in a way that you're going to be able to use it."
	"You may have to engage with some third-party vendors that may provide the necessary hardware or software to accomplish your goal."
	"There's external consultants, probably technology would be the biggest one, I would say."
Demonstrate individual impact	"And I think the reason we have people so engaged and their engagement level is high, is we've involved them from the get-go. We've made it interesting. We haven't made it a punishment. They're getting things from there and getting things out of it."
Data proves itself	"It's going to be difficult to persuade anyone to do anything without supporting data."
	"If they don't like what it's saying, it's hard. But if you can prove it to them and you can show them how to drive their numbers in the right way by the changes they make…"
	"I don't even know where you'd begin to sell that. The only way I would know is to formulate examples of where the data is correct."

> "That's when you actually prove your analysis, by being right and making people make decisions surrounding what you said in your analysis."
>
> "If someone's got their mind set on something, especially if it's someone that's in a superior position than you, it's pretty difficult at times to, even with the best data, to drive your point across. But I think what it boils down to many times is, if you can somehow prove that there's a cost savings or an incremental increase that's going to influence your bottom line better or your productivity better, I think that's how you have to approach it.

Relationship of Subthemes to Teamwork and Team Management. Trust in nominal data values and trust in analyst outputs are related in many ways to team design and teamwork. Many of the elements of technical buy-in and persuasion foreshadow the need for organizations to promote cultures of teamwork and collaboration. Leadership styles are important to the promotion of culture; organizational leaders should promote cultures that encourage teamwork and foster trust (Akaegbu & Usoro, 2017; El Khouly et al., 2017). Collaboration and teamwork between data-driven teams and their customers are critical to obtaining the trust necessary to create a productive environment (Akaegbu & Usoro, 2017; Gannon-Slater et al., 2017; Knapp, 2016). Several participants discussed the need for a healthy work environment, stressing the relationship between teamwork, trust, and results. Participant 10 indicated that in a data-driven environment, employees are working on larger teams and must have a high degree of trust and respect for one another:

> There's got to be a huge amount of teamwork, a huge amount of trust between the team. Collaboration is… you have to be collaborative in that type of setup, because you're pulling information and resources from so many different areas.

Trust between members of an organization is critical to developing the desired data-driven culture. Without this trust, an organization is unable to produce the results expected of a data-driven company; without this trust, the business cannot persuade leaders to use data-driven technologies. A mature organization with regard to data-driven decision-making is one that has high confidence in its own data and its own analysts.

Theme 2: Design of Culture and Teams

Conversations with participants revealed much about the organization's concept of the design of data-driven cultures and teams. Topics were generally categorized into (a) design of team culture, (b) design of teams and the assignment of employees to teams, and (c) the cultural transformation process. In discussing team culture, participants described the teamwork element of culture that is required to develop a data-driven environment, notably discussing the wide scope of organizational culture and the goals and expected results of such a culture. Participant beliefs concerning team design largely supported a cross-functional, diverse design, with occasional consultant involvement and highly-skilled team members. Participant discussion of cultural transformation was somewhat inconclusive, with participants split between who is responsible for changing culture. Conversation regarding the process of cultural transformation yielded positive results and led to the development of seven steps by which organizations may change their culture to one that is more accepting of data-driven decision-making.

Subtheme: Design of Team Culture. Leaders aiming to create a culture of data-driven decision-making must first design the culture they seek. According to participants, taking time to properly design and promote culture is necessary for achieving a higher degree of data maturity. Leaders must consider various perspectives of culture, including its scope, how to achieve buy-in, responding to turnover, and the intended results of the new design. Leaders should also ensure involvement of key stakeholders to help promote trust among the new team organization.

Data strategists and those looking to promote a culture of data-driven decision-making should first understand the scope of culture. This first involves recognizing that *culture spans organizations*. Participants consistently indicated that company culture covers all employees and does not ignore certain individuals or departments. Mesaros et al. (2016) explained that culture must be consistently implemented across the full organization. Villamarin-Garcia and Diaz-Pinzon (2017) described culture as a part of the overall internal environment and show that this environment can be a catalyst for organizational change. Cekuls (2015) addressed the specifics of a data-driven culture and explains that such a culture should promote initiatives to all members of the business. Four of the 18 participants, or 22%, noted that culture is not limited to a single group of employees. Participant 5 explained that all members of an organization must be involved in implemented a data-driven culture: "I think everyone internally, if you're going to have a data-driven culture, everyone needs to be involved."

Implementing a culture only partially can have unintended consequences and present challenges that may be difficult to overcome. Some participants explained that culture bleeds into surrounding areas of the organization and that aspects of culture cannot be limited to a single department or individual. Participant 10 describes the difficulty of implementing culture between only a subset of organizational employees:

> The other thing is, if you start running projects on two fleets… you're talking about changing culture, changing the makeup of those individuals. How are you going to change them and not isolate the others? They'll be drug along on the journey either way.

As cultures are transformed and actions are suggested or completed by top-level management, observing such actions being repeated at lower levels of the organization is indicative of a successful culture transformation. Participant 16 explained that a culture can be evaluated by noting if middle managers begin exemplifying the desired behaviors:

> I really think it's when the next level down, your first level or second level management, when they take the ball and start running with it. And it no longer needs to be suggested or driven at the executive level. That's how you know change has come into effect. And I'm starting to see signs of that all over the place.

Knowing the scope of a culture transformation and understanding that such efforts must be conducted across the entire company can help agents of change plan for future actions. This helps create a cohesive strategy for transforming culture and helps promote unification throughout the organization.

In creating a data-driven environment, organizations must also ensure that all employees are operating with a *common goal*. The goals of every individual should work to support the overall goals and strategies of the business. Maintaining a unified goal and a common purpose promotes the idea of teamwork and is a necessary component of creating a data-driven culture. Stacho et al. (2017) explained that the environment of an organization influences employee behavior and that behaviors should be tailored to fit the company's overall strategies. Five participants of the 18 in the study, or 28%, stated that companies should ensure that a common goal is part of the organizational culture. Within their own organization, participants explained that culture is developed with the input of all members of the organization. Participant 2 described the process of developing culture, stating, "[We] got everyone to contribute to what we wanted the culture to be." Furthermore, goals and culture must inspire confidence in the organization's employees. Participant 4 described the importance of agreement and belief in culture among staff members: "Whatever culture you implement, it has to be a culture that everybody believes in and everybody can agree on."

Possessing a common goal involves all employees understanding the importance of organizational metrics and working together to meet those goals. Participant 18 described the details behind the purpose of a common goal and the actions employees must take to be part of the team:

> For us, if we could speak the same language, which for me is… what are our goals? What are our lead measures? What are the activities we need to be conducting to achieve those goals? And there are those other departments, more on the soft side: the minds, the hearts, the spirits of the people.

Building culture around common goals helps align members of the organization and foster a sense of community and teamwork. This is a crucial step in building a data-driven environment and promotes the important ideas of trust and collaboration.

When new employees are brought into the organization, or when cultures are modified and must expand through a business, employees must *assimilate to the culture*. Participants explain that many cultures fail to gain traction due to a lack of buy-in among employees. In many cases, these employees are long-time workers who have a negative outlook toward organizational change. When promoting a new culture, Lewis (2019) discussed the need for including professional development and employee onboarding in a strategy. This indicates that individuals who hope to remain or become part of the business must buy in to the organization's culture; those who choose not to assimilate would likely be more suitable for another company. Three participants of the 18 in the study, or 17%, described the need for assimilation among new and existing employees. Participant 8 explained that employees must become part of the culture of the organization to best affect change and most effectively serve the business: "Sometimes you just have to drink the Kool-Aid and go forward and move with what needs to be done in order to affect the changes that are necessary to change that culture."

Several participants discussed the challenge of winning over long-time employees. These employees are often settled into their positions and can, in some cases, be difficult to persuade to change processes or beliefs. Participant 4 explained that if employees cannot accept a new culture, employers must ensure that their replacements are willing to adapt to the chosen values of the organization:

> You've got some out there that, especially some of the older ones that have been in the company for a long time, do things a certain way for 30, 40 years and it's never going to change. Those people just have to leave through attrition, whether they retire or whatever, but if you're not going to get them to buy in or change their mind, then their replacement will have to buy in.

Participant 9 corroborated this stance, explaining that an individual's worldview and experiences may affect their ability to adapt to a specific culture:

> Some of it, honestly, is moving to a different set of people. Different mindsets of different people, they may adopt easier than others, or shift people around so they adopt in different ways, those are some of the key elements for changing culture.

Ensuring that all employees assimilate to the chosen culture, regardless of the design of the culture itself, helps organizations create a cohesive set of employees that can work together as a team to achieve organizational goals. Businesses are best suited by earning the buy-in of existing employees, but organizations should expect to see a certain degree of turnover when changes are made. Organizations must respond to this turnover by replacing employees with those who can adapt to the chosen culture and contribute in a positive way.

A close corollary of assimilating to the culture, *cultural buy-in* refers to the need for organizations to earn the trust of employees and convince staff to agree to changes in the culture. Without this crucial trust, leaders cannot inspire employees to conduct tasks related to the desired culture. This was a popular topic among participants, with most agreeing that cultural buy-in, in the sense of data-driven decision-making, contributes to data maturity. Researchers consistently explain that cultural buy-in enterprise-wide is a crucial aspect of becoming data-driven (Grubljesic & Jaklic, 2015; Halaweh & El Massry, 2015; Mesaros et al., 2016; Mikalef et al., 2018; Yeoh & Popovic, 2016). When discussing a data-driven culture, eight of 18 participants, or 44%, identified cultural buy-in as an important component of cultural transformation. Participant 6 affirmed the need for obtaining cultural buy-in and its relationship to enthusiasm for organizational initiatives: “A data-driven culture, I think the biggest thing is, you’ve got to have people involved and they’re got to have some buy-in to the process in order to have some belief in the process.”

Obtaining buy-in is an early step in transforming organizational culture, though frequently organizations must design their team-centric culture around buy-in and the nature of trust within the business. Participant 11 described that often companies must institute processes and policies according to the general buy-in for the desired culture: “You have to have the buy-in of the organization, then you have to develop that infrastructure and start basing the management of the business on that model.”

As previously alluded, buy-in to a data-driven culture is often correlated with data maturity. Organizations whose employees subscribe to a data-driven culture are frequently more mature and are significantly more capable of progressing further along the maturity curve. Participant 5 described a prior organization where the participant experienced the relationship between buy-in and maturity first-hand: “One of my previous employers, we had a data-driven culture, and we were actually transitioning, and we had buy-in from everyone. And the more buy-in we got, the more mature we got, the more they trusted their decisions.”

One participant was somewhat pessimistic toward the idea of buy-in to a specific culture. Participant 3 stated that the organization can sometimes fail in terms of execution of data-driven strategies despite good intentions:

> I think if you get buy-in from a certain group of people, then I think that group of people will be closest to the ones driving it, but the further you get down the chain, I think it gets lost.

Despite occasional dissention, participants consistently described the necessity of buy-in and its relationship to data maturity. Participants painted a clear picture of the scope of culture, explaining that culture must always span the organization, leaders must identify common goals, and employees must assimilate and buy-in to the culture. These principles contribute to leaders’ understanding of the design of team culture and ultimately the decisions leaders must make with regard to building and transforming the culture of their organization.

During the development of a data-driven team culture, leaders must make several considerations. In particular, turnover can create a major problem for cultural transformations, especially if turnover occurs in leadership roles. Because culture is often tied to a particular leader or leadership team, turnover can create disruptions that can be difficult to overcome. Three participants of the 18 surveyed, or 17%, described the *effect of turnover* as a disruptive event. Participant 9 discussed the need for stability in management positions, inferring that changes in management can lead to changes in policy: “And our management sticking around. That’s another thing, if our management is staying around in addition to the numbers and our executive team is pushing forward, I think that’s probably showing some good signs.”

When leadership changes become too frequent, and especially when executive turnover becomes dysfunctional and toxic, data-driven projects can suffer immensely. Participant 6 described the reasons behind this, indicating that new management may have different opinions concerning data usefulness or may not understand the ways information is transmitted through the organization:

> I think too often, sometimes leadership changes and stuff like that, creates such a drastic change that they feel like they… some people don’t believe in the data, don’t believe that it’s necessary, and so you go back and forth. […] And it just falls by the wayside.

The effect of turnover on data-driven cultures is not limited only to executive positions; turnover in analyst or data science roles can threaten the culture as well. Participant 8 explained that turnover in technology positions can be disruptive due to the complex nature of the work: “As you know, whenever you change data scientists or programmers, there’s a learning curve. There’s a delay on the information that can be provided, because the individual that programmed those programs are the ones that understand how they go.” Finding ways to reduce turnover and minimize its impact can help transitions run more smoothly. This helps protect data-driven cultures against gaps in knowledge and uninformed decision-making that may arise during transition periods.

Part of the design of a team culture involves supporting *moral and ethical decision-making*. New technologies are a breeding ground for new ethical quandaries that must be considered. Leaders should promote ethical decision-making to ensure that when analysts and data scientists are presented with unfamiliar situations, they may select the most moral and ethical option. Giffone (2019) and Kirkpatrick (2019) explained that technology is often used as a means to an end and warn that both the “means” and the “end” should be ethical. One participant mentioned the morals of data-driven decision-making, explaining that these must be considered before allowing data to drive decisions autonomously: “I think that’s one of the challenges of AI, is that if AI only relies on the data and the facts, then what are they going to do in a situation such as a moral dilemma?” Organizations must be careful to maintain their guiding morals when becoming data-driven. Technology sometimes tempts practitioners to dehumanize individuals. Analysts and leaders must be careful to avoid this when instituting a data-driven culture; building ethical decision-making into the culture definition is sometimes a necessary step to prevent immoral actions from being taken.

A team culture of data-driven decision-making should be implemented with various goals and results in mind. Participants identified five unique outcomes of team culture that each contribute to the ability of the team to work together in developing a data-driven environment. These outcomes include (a) accountability, (b) servant leadership and service culture, (c) trust in the environment, (d) celebration of accomplishments, and (e) understanding one’s own contributions to the organization. When a culture includes these concepts as outputs, a logical consequence is a more trusting environment with the ability of employees to work together as a cohesive unit.

The first outcome of team culture, *accountability*, refers to the organization’s ability to hold employees responsible to their outputs. This involves ensuring employees are liable for their performance from the individual workers to the top-level managers. In a cohesive team culture, individuals are held accountable to their performance goals as well as their promised outcomes.

Gannon-Slater et al. (2017) explained that a culture of accountability is necessary for organizations looking to become data-driven. Four of the 18 participants, or 22%, discussed accountability as a necessary component of a data-driven culture, specifically as an output of the team culture instituted by the organization. Despite often carrying negative connotations, participants tended to refer to accountability as a device that can be used to coach employees and drive better, more productive behaviors. Participant 16 explained that accountability can be used as a way to generate competition among employees and to help understand areas of improvement for individual workers: "It's coaching through data. It's using data to measure someone's performance, and to put it out there and create healthy competition, and all the good things that come from data." A culture of accountability helps encourage the creation of goals. Participant 9 describes how a team culture of data-driven decision-making helps to create goals: "And also, for the predictive portions and the things that help us make decisions, it helps us to meter those things and create goals and things around it." Accountability, as an output of team culture and an input of trust and data maturity, is sometimes controversial but often a useful tool in a culture transformation. The link between accountability and trust is strong, ensuring that this trait is highly useful in creating a data-driven culture.

Some participants discussed the need for adopting a *service culture*. A culture of this nature emphasizes service to others, whether internal or external to the organization. Gioti et al. (2018) and Lehrer et al. (2018) showed that there may be some reciprocity involved in this relationship, indicating that data-driven cultures promote better service. Two participants, or 11%, noted the need for adopting a service-oriented culture to grow the team-centered approach needed in a data-driven environment. Participant 12 explained that leaders should adhere to the principles of servant leadership: "I think a good culture… I've always adopted kind of the servant leadership culture. Treat others like you're their servant in all capacities." This worldview applies to employees across all levels of the organization and should inform interactions with superiors, peers, and subordinates equally. Participant 4 discussed the importance of adopting a service mindset when interacting with customers and applied the principles of service culture to technology: "Our customers see technology as a way of making it easier to do business with people. And so, to a company that doesn't want a data-driven culture to improve, they're going to end up losing customers." Developing a team culture should lead to better service across the organization and helps foster the sense of teamwork that is necessary to build a data-driven culture. This teamwork and trust is an integral factor in building data maturity and driving the desired form of decision-making in the business.

Team members must project a certain level of trustworthiness, but they must also be able to demonstrate trust in their fellow workers. Participants explained that members of a team must be able to trust one another and their collective environment. This trust allows team members to focus on their own tasks and work better as a larger entity, in the sense that the whole is greater than the sum of its parts. Mesaros et al. (2016) showed that members of a business intelligence team should trust each other and work in a cooperative environment to achieve some degree of success. Two of the 18 participants, or 11%, called out the importance of allowing oneself to trust their peers. Participants explained that trust in others and *trust in the organization's environment* can enable progress in data maturity. Participant 10 explained that a lack of trust is a barrier to advancement in data-driven projects: "There has to be a level of trust there, otherwise nothing else will ever develop. So, accountability cannot be developed if you do not trust one another."

Participant 17 expanded the scope of "trust" to include the internal environment. This participant explained that a good work environment facilitates additional progress:

> I think work environment is a big thing. Nobody wants to go to work and be miserable. I think if you've got a good work culture and environment and you're flexible with the way you operate, you're pretty casual, it's a good work environment. It's not toxic. I think it's good.

Building an environment in which employees can feel comfortable, as well as ensuring that employees are demonstrating the desired level of trust, is a significant influence on a culture of teamwork. Because such a culture is necessary in building a data-driven environment, this trust in the environment is a component of data maturity that cannot be ignored.

When business intelligence teams deliver results that have a positive impact on the organization, team members and organizational leaders should occasionally pause to *celebrate accomplishments*. These brief recognitions serve to provide both praise for instrumental individuals and publicity for the successes of the project. Celebrating the accomplishments of high performers motivates them to continue their work, while providing opportunities for other team members to improve. Furthermore, recognition may occur at a team level in a public setting to help drive organizational support for the team's work. According to Foster et al. (2015), data science teams should identify areas for early victories and ongoing successes, then publicly demonstrate the impact of their work. This presentation encourages business leaders to continue investments into the team (Foster et al., 2015). Of the 18 participants in the study, three (or 17%) discussed the need for celebrating the accomplishments of their business intelligence teams. Participant 10 stressed the importance of celebrations taking place in a public forum and that they should be focused on results: "You have to celebrate the wins. The benefit of the projects that come out of a data-driven culture have to be visible to everybody." Celebrating the victories of the team, or individuals within the team, is intended to develop the culture of teamwork required in a mature organization. Participant 12 discussed the relationship between employee recognition and team morale:

> I think a leader also has to stand up and take… I think they have to give the attaboys. The praises deserved. Because I think that a leader needs to build up the team, and not be the one that tears down the team.

Leaders who focus on the positive work of data-driven teams will build more successful team cultures than those who focus on the negatives. According to participants, if the organization works to recognize quality work of employees, teams are strengthened and organizational work output improves.

The final aspect of creating a team culture, *understanding one's own contributions*, was a somewhat popular topic among participants. In particular, participants indicated that members of a team must know their worth and understand how their work contributes to the team and the overall organization. The surveyed organization has internal processes to ensure that all members of the business understand how their job function contributes to the financial performance of the company. Five of 18 participants, or 28%, discussed the necessity of understanding their contributions to the organization. Participant 15 explained that employees should know how their job roles fit in the larger organizational context: "Communicating or transmitting the information needed to the end users so that they know what their day-to-day job… how does their day-to-day job contribute to that overarching goal for the company?" Participant 13 provided additional detail regarding the way the organization communicates these concepts to employees, and how individuals should react to this understanding:

> It comes back to, when you start doing these money-making models, how each person contributes to these certain, whatever if identified as the biggest impact you can make, but how you as an individual contribute to that, and I think that's where your analyst can be equipped by… here's what this group can impact, here's what we need to look at.

When individuals understand their place in the organization and how their contributions affect their fellow workers, they become more engaged and are more likely to make positive contributions to the business. This helps build a sense of a cohesive team and encourages members of the organization to have stronger trust in one another.

Defining the outcomes of a team culture is an important step in building the desired data-driven culture. Understanding the goals of a culture transformation helps the organization know what steps it must take to become more team-oriented. Participants identified five desired outcomes of a team culture, all centered on the need for growing trust among team members. Outcomes included (a) accountability, (b) service culture, (c) trust in the environment, (d) celebrating victories, and (e) ensuring that every employee knows their worth in the company.

Participants frequently commented on the necessity of business intelligence teams working with their target audiences when developing solutions. This was a common theme with a clear consensus among participants in the study. Working with end users before, during, and after development of decision-making tools helps promote trust and adoption of the product and helps target audiences better understand the information they are receiving. Researchers consistently encourage business intelligence teams to involve end users throughout development processes, resembling agile development methodologies (Grubljesic & Jaklic, 2015). When teams include members of all areas of the business, members from various departments will help the groups they represent to provide additional trust to the process, creating a sort of grassroots campaign to increase trust in data-driven decision-making (Skyrius et al., 2016). As a significant part of the development process, involving the target audience helps analysts and data scientists earn trust before solutions are provided to end users (Grubljesic & Jaklic, 2015; Mesaros et al., 2016; Skyrius et al., 2016; Yeoh & Popovic, 2016).

Participants frequently mentioned *user involvement* as a critical activity of business intelligence teams that helps to foster a sense of overall teamwork between members of the smaller team and members of the organization. Of the 18 participants in the study, 11, or 61%, discussed the need for user interaction prior to and during the development process. Participant 10 took an extreme stance toward user involvement, stating, “You have every employee as a stakeholder.” Participant 8 described stakeholder involvement in terms of project management, explaining, “I’ve been extremely successful at it because I bring all aspects of business into my project management.” Furthermore, Participant 15 showed that one purpose of user involvement is to properly understand their needs, explaining, “I think it’s engaging the stakeholders to understand what they need to run their business.” Some participants focused the need for user involvement on ensuring that the delivered product matches the needs of the audience. Participant 6, for example, explained that a business intelligence team should first understand the needs of the organization before building a solution:

> You’ve got to have the users to help you to understand what they’re after, because in the end, we can create some reports and put the data together, but if we don’t have an understanding of their end goal, then we may not put the data together in the right way.

The comments of participants with regard to user involvement foreshadow the need for analysts to build relationships with decision-makers in the organization. Building this relationship helps create a culture that supports trust in technology and, ultimately, data maturity. Participant 7 elaborated on the relationship of analysts and end users, including the need for continuous, prolonged engagements and participation from users:

> And then also just, and before we even get started on a project, just making sure we're on the same page and not just trying to briefly describe something but actually trying to understand the details and sitting down with him and discussing it. Some of the smaller details that are going to have a big impact on whether it's going to be a report or an analysis. So, I guess patience, and him making the time to follow up on anything he's asking for.

This indicates the need for willing stakeholders to work extensively with analysts. Although user involvement frequently is limited to a small number of discussions at the beginning of a project, participants noted the need for ongoing engagements that cover the definition of a project, its implementation, and its deployment. Participant 10 called out the usefulness of such prolonged relationships:

> I think there needs to be an integration with the teams. I'll use [R.] as a good example again. So, he was a business analyst. He had been in the logistics industry before he did that, so he knew a little about it and then he was significantly engaged with the team. He was almost an employee of Logistics, not Finance.

Continuous involvement with the target audience helps a business intelligence team deliver more accurate results. A secondary function of this involvement enables the team to make inroads with potential users prior to the deployment of a solution. Participants described the benefit of involving decision-makers in product development and the propensity for these users to adopt technologies once they are made available. Participant 16, when discussing the ways user involvement leads to increased trust, had explained the theory that prolonged engagements leads to a higher likelihood of adoption. To restate, this participant had developed the *Field of Dreams* theory: “They’ve got to help build the field, and then they’ll want to play on it. They help you build your dataset and they’re helping you build the use cases and they’re helping you validate them.” The theory that individuals who help develop solutions are more likely to adopt them is explained by Participant 6, who argued that user involvement indicates an investment on the part of the stakeholder: “I think you’ve got to have them involved in some way or fashion to get them some ownership of it.” Several participants noted that despite user involvement being an invaluable part of the culture of teamwork leading to a culture of data-driven decision-making, users do not necessarily need to be part of the business intelligence team. Although some participants encourage data-driven teams to include stakeholders, others argued that they should be involved on an as-needed basis. Participant 18 explained that a stakeholder is defined as an individual who is affected by a business process: “I think… this is very similar to what you do in any process improvement project. You bring stakeholders from every department that’s affected by the process.”

Participant 12 indicated that business stakeholders could be useful as an occasional resource, but that including them as part of a core business intelligence team would be inappropriate:

> I don’t know if you would necessarily want to involve someone directly on the business side, other than just maybe someone like an Operations manager or someone like that. But just as an outside resource. Someone you can ask pointed questions to. But I don’t think they would aid you by being directly on the team, because a lot of what you’re doing is not necessarily in their scope of knowledge.

Participant 17 cautioned against naming individuals as stakeholders in a project simply because of job title or department membership, explaining that experience and influence are far more useful qualities: “You need a heavy IT presence, you need a heavy Operations presence, and you need to pull in… I don’t know that we necessarily pulled in different departments, we pulled in people with a lot of experience.”

Regardless of the semantics of team membership, all participants who discussed user involvement agreed that business intelligence teams should work with organizational decision-makers while developing new analytical systems. According to participants, this integration with the operations of an organization helps improve both the quality of analytical output and the likelihood of its eventual adoption and acceptance in the company.

Designing a team-oriented culture is an important first step in building a culture of data-driven decision-making. According to participants, this helps provide a foundation and gives business intelligence teams their best chance at improving an organization’s data maturity. Participants described the far-reaching scope of a team culture as well as the ways its outputs can set the stage for enabling data-driven decision-making. Furthermore, participants consistently stated that teams should engage with key stakeholders on an ongoing basis to ensure both quality of analytics and adoption of technologies. Participants frequently layered the concept of trust into discussions of team culture and explained that this was the ultimate foundation of team-based business intelligence projects. Additional supporting statements from participants are given in Table 3.

Table 3

Identified Themes and Supporting Statements – Design of Team Culture

Identified Theme	Supporting Statements
Culture spans organizations	"'I want you guys to learn this stuff and have it ingrained in you, and once it's ingrained in you, it's ingrained in the people below you,' and once it's ingrained in those people it's ingrained in the people below them, and before long it's like a pyramid scheme. It flows from one person to the next."
Common goal	"Everybody being on the same page as to what the end result should be."
	"I think having one purpose or one goal for the organization."
Cultural buy-in	"I think you need trust and people have to like or want to follow your vision, the overall vision."
	"As long as everybody is buying in and believing that process and following it, that will allow you to maintain that consistency, that culture of being data-driven."
	"They have to be bought into the project. There's nothing worse than being a project and somebody's not bought in, they're not contributing, and it can leave a hole in an otherwise successful project."
	"I think one of the first things you have to look at is… how is the buy-in? Was the change accepted?"
Effect of turnover	"There's also the risk that management could change, decisions could go a different way."
Accountability	"People are held accountable to the numbers, and I think it drives people to focus more on data."
	"I think the only way to get buy-in in that situation is to force accountability of, if you make a decision, it has to make sense afterward. The math has to make sense after you make the decision, and you hold them accountable to that."
	"I think that accountability is always going to be a huge thing."
Celebrate accomplishments	"It's where you're missing the boat, and then using data when you do well to celebrate your wins."

Understanding own contributions	"It's got to be real-world application for them, so, I think it starts with education on what's going to occur with the data, and you've got to educate on where the data is coming from, and help them understand how the actions that they take… you know, it starts with them."
	"Everybody has to know how they're a key component of that."
User involvement	"And once you give them things they can use, they get anxious about the next one. Because if you give them something really good that they can use, then they think, 'I can't wait to see what we can do when we really get this thing going.'"
	"Mainly just communicating with who your data is going to be presented to and then understanding what they need to see on a day-to-day basis to manage their business."
	"You have to work with your business owners because you have to understand what their needs are."
	"And then you've got to have the consumers of the data helping you build it and helping you produce your quick wins, so that's key."

Subtheme: Team Design and Population. When designing the structure of a team, participants noted that the organization should strive to populate the team with the correct members. Team design was discussed by 17 of the 18 participants in the study, or 94% of participants. Participants had a variety of differing opinions regarding team structure, though ultimately appeared to reach a consensus. Most participants fell into one of three camps: (a) IT-driven solutions, (b) financial or analyst-driven solutions, or (c) team-driven solutions. The majority of these participants eventually preferred team-driven solutions. Participants frequently agreed that team members should have a diverse set of backgrounds and skills. When asked to discuss the skills necessary to create a data-driven analytics team, participants provided a laundry list of technical, leadership, and soft skills and largely provided a well-rounded collection of useful qualities.

Participants discussed team composition at length, generally believing that business intelligence teams should be driven by IT groups, groups of financial analysts, or by a mixture of IT, analysts, and other stakeholders. Belief that solutions should be led by one of these groups did not necessarily indicate that the participant felt other groups should be excluded. Furthermore, a small number of participants discussed more than one methodology or felt that the primary team composition was not a strict rule in team development. Researchers generally sided with the team-based approach to team design. Ylijoki and Porras (2016) explained that business intelligence solutions are enabled by IT resources utilizing the necessary technologies and talent. Researchers emphatically state that IT involvement is a non-negotiable aspect of a team, but that these technical resources cannot, by themselves, deploy a solution to the organization (Halaweh & El Massry, 2015; Jabeen et al., 2016). On a wider scale, Jabeen et al. (2016) stressed that IT resources are unable to single-handedly accomplish the goals of data maturity. Instead, researchers generally agree that business-oriented team members should work to drive adoption of data-driven solutions within a company (Ylijoki & Porras, 2016). Chen and Nath (2018) explained that adoption of technologies is best suited by a technical team supplemented with organizational involvement, including some managerial and executive support. Yeoh and Popovic (2016) summarized team composition by stating business intelligence teams are most useful to the organization when consisting of a combination of business and technical resources, as well as a project champion and an experienced external consultant. This diverse set of individuals comprising a cross-functional team builds trust within the organization and helps usher in a sense of community (Skyrius et al., 2016).

Five of the 18 participants in the study, or 28%, discussed to some degree the concept of *IT-driven solutions*. Two of these participants represented the IT department, or 29% of the seven IT individuals surveyed. Two participants in this group represented the Finance department, or 67% of the three Finance employees interviewed. Participant 12, a member of IT, was a proponent of IT leadership in business intelligence teams, stating, "I think it's going to be highly IT-driven." Participant 14, also a member of IT, proposed a partnership between IT and stakeholders in the organization: "Definitely IT and key users. And, of course, whether that be internal tools that we develop or external, like Power BI, for example… but definitely it would be IT and key business users." Participant 14 also discussed the potential for teams to be analyst-led. Participant 4, an employee in a financial role, discussed a similar arrangement, indicating that IT-driven teams should involve all departments in the organization in their efforts: "I think in terms of partnership, you have to start with your Information Technology group, and I think your Information Technology group has to go to every single department that enters data into the system." Similar to Participant 14, Participant 4 discussed alternative strategies as well; Participant 4 also proposed a better well-rounded team structure. Despite a significant number of participants discussing solely IT-led business intelligence teams, three of the five (60%) participants also discussed other methodologies, with only two participants floating only the idea of IT-driven solutions.

Three participants, or 17% of the 18 surveyed, discussed *analyst-driven solutions*. One of these participants occupied a financial role, representing 33% of the three finance-oriented participants. Two participants in favor of this plan represented IT, making up 29% of the IT employees surveyed. Participant 2 discussed the need for financial individuals to provide an unbiased analysis of data: "I think analysts are necessary or at least some form of a person that can wade through the data in an unbiased way and create and actionable decision for the business." This participant also suggested team-based solutions as a potential design. Participant

3, a member of IT, explained that only analysts should be involved in business intelligence teams, explicitly stating that IT resources should be involved from a support perspective only: "I think anybody that's working with data, or writing reports, or making decisions, or compiling, should be in some form of an analyst role. […] To me, IT is just the implementer." Participant 3 was the sole individual surveyed who believed that business intelligence teams should be analyst-driven; two of the three participants (67%) who discussed the possibility of analyst-driven solutions also discussed either IT-driven solutions or team-driven solutions.

The majority of individuals interviewed, 13 of 18 (72%), agreed that business intelligence teams should be made up of individuals in both IT and analyst roles, as well as potential stakeholders in projects, as a robust *team-based solution*. Of the seven IT individuals surveyed, four, or 57%, discussed the need for team-driven solutions. In members of the Finance organization, all three (100%) called out the usefulness of cross-functional teams. Among the four Operations personnel, three (75%) discussed this need, while all three members of the leadership team (100%) that provided an opinion supported team-driven solutions. Several participants discussed the need for a formalized, cohesive team that works together to build data-driven solutions. Participant 10 explained that business intelligence teams may have a core group but that the team should be a collection of diverse individuals: "In our case, it's going to be a collection of people that create the team. There may be a core team or a core individual, but the actual project team is going to be a collective group." In addition, Participant 8 acknowledged the challenges associated with creating a cross-functional team, noting that teams working on business intelligence solutions should work in nearby areas where possible:

> I think that's where the partnership needs to come, and like I said earlier, bringing those departments to be more interactive with each other instead of being separated by literal walls or floors, are going to help benefit and help change that culture.

When discussing team composition, participants who suggested a cross-functional team frequently mentioned IT and analyst roles. Participant 9 discussed building a dedicated cross-functional team tasked only with building business intelligence solutions, made up of individuals with backgrounds from both areas of the organization:

> I think it should be its own team. Yes, I think there's some IT involvement of course, and there's analyst involvement of course, but I think that you could take key members from different roles. Definitely Finance roles. Anything like that can pull into one group and have one big strong team to help drive the whole project.

Participant 2 elaborated on this stance, explaining that financial analysts are needed due to the frequent financial nature of data and the ways that organizational metrics affect the profitability of the company:

> I think analysts and IT work hand-in-hand. There's a reason that they go together in a lot of organizations. I think both of those and then also I think Finance in general ties into those because you're usually looking at financial data and how stats drive financial data.

Some participants discussed the inclusion of other representatives. These representatives are not necessarily stakeholders but possess knowledge and skills necessary to contribute to the quality of the team's output. Participant 16, for example, identified executive leadership and process managers as being necessary for team success: "You need IT, you need [Financial Planning and Analysis], you need [reporting]. I would say your business unit managers, and you need executive sponsorship. And you probably need your process people to help you define your processes." Participants resoundingly reached the conclusion that business intelligence teams should be made up of a diverse set of individuals with a mixture of technical and analytical backgrounds. Participant 7 discussed the purpose of this assortment, explaining that analysts can help validate solutions and help demonstrate actionability to otherwise skeptical decision-makers: "Good IT, good data analysts that build the reports and vet the accuracy of the reports, and then other parts of the organization like [Financial Planning and Analysis] can use them in order to actually have recommendable actions." Some participants explained that individuals tasked with building data-driven teams should not make decisions on team membership solely on job title or department. Participant 6 stated that leaders should search for individuals with diverse skills: "I think you've got to have a certain number of people, depending on how large the project is, that have different skillsets." Participant 17 elevated the need for using experience to determine team composition, noting that some individuals have diverse backgrounds and may be useful in the project regardless of current job role.

Several participants explained that stakeholders, or business personnel, should be included in cross-functional teams as core members. Participant 15, for example, stated that business intelligence teams should consist of members across the business to reduce the likelihood of barriers and to improve the diversity of ideas within the team:

> I think it needs to be a cross-functional team, both with the front-level Operations staff from the business units, obviously some folks from the IT side, from Finance, depending on the project, folks from Procurement, Safety… really a cross-functional team across the organization to make sure there are no roadblocks or barriers and to make sure that you get a very wide-ranging perspective on the project.

Participant 13 further discussed the need for involving business users in the process, explaining that these users are the only individuals in the organization who have the intimate familiarity with data needed to fully understand an issue:

> I think you have to have some of your front-line people in there. I think they're the ones that are down in the trenches every day. In a lot of cases, I think they already know or have some type of solution to the problem, we just don't give them credit for being creative and coming up with them.

Ultimately, involving stakeholders as core or even ancillary members of a data-driven cross-functional team is a necessity that helps improve the accuracy and adoption of data-driven technologies. Participant 4 succinctly stated that, because the entire organization needs information and that everyone is affected by data processes, all departments must be represented in some form in a cross-functional team aimed at transforming data maturity: "I think you would probably need a representative from just about every department because every department is going to have a hand in using that data." Although project work always requires user involvement, establishing stakeholder interaction with wider data-driven initiatives improves the ability of organizations to transform culture and drives further adoption of technologies among decision-makers.

Although some participants discussed the need for IT-driven solutions or analyst-driven solutions, 13 of the 17 participants (76%) who expressed an opinion concerning team composition explained that teams should be cross-functional in nature and be driven by several different key individuals. Of the seven participants who recommended either IT or analyst-driven solutions, three (43%) followed these recommendations by statements in support of team-driven solutions. According to the majority of participants, cross-functional teams comprised of IT representatives, financial and business analysts, and key stakeholders are the most effective form of team composition when the goal is improving data maturity in an organization. Table 4 outlines the opinions of each participant, providing both their own department and their preferred data-driven team composition.

Table 4

Participant Beliefs on Team Composition

Participant	Department	Ideal Composition
1	Operations	IT-driven solutions
2	Finance	Analyst or team-driven solutions
3	Information Technology	Analyst-driven solutions
4	Finance	IT or team-driven solutions
5	Information Technology	Team-driven solutions
6	Information Technology	Team-driven solutions
7	Finance	IT or team-driven solutions
8	Leadership Team	Team-driven solutions
9	Information Technology	Team-driven solutions
10	Leadership Team	Team-driven solutions
11	Information Technology	Team-driven solutions
12	Information Technology	IT-driven solutions
13	Operations	Team-driven solutions
14	Information Technology	IT or analyst-driven solutions
15	Operations	Team-driven solutions
16	Leadership Team	Team-driven solutions
17	Operations	Team-driven solutions
18	Leadership Team	None specified

Ultimately, according to participants, business intelligence teams are best served by a diverse set of individuals comprising a multitude of backgrounds. This is consistent with the research of Lewis (2019), who states that diverse groups are best prepared to transform organizational culture. Furthermore, Skyrius et al. (2016) explained that cross-functional teams are best equipped to project trust throughout the organization, especially when such teams include representatives from all areas of the business. Participant 15 implored leaders to “make sure that you get a very wide-ranging perspective on the project.” Similarly, when discussing an existing cross-functional team in the host organization, Participant 17 stated, “We pulled in people with a lot of experience.”

Participants also mentioned consultants in discussing team composition, despite such individuals not being part of the organization itself. Yeoh and Popovic (2016) concurred with this stance, stating that business intelligence groups are most successful when consisting of a diverse set of internal resources and an external consultant with prior experience. As discussed in Theme 1, nine of the 18 participants, or 50%, agreed that external technical consultants could be beneficial in sparking organizational trust in data-driven initiatives. Participant 3, for example, explained that external consultants can help design outputs into useful, unbiased products: “Externally, there may be a resource to help you compile that data into something that’s useful, maybe as a third-party person that is looking at it from the outside in, to give you an unbiased approach.” Participant 6 took a similar stance, explaining that consultants can assemble data on behalf of the host organization, based on the needs of the company: “You’ve got to be able to work with the third-parties in order to have them compile the data that you need, then be able to give it to you in a way that you’re going to be able to use it.” Similarly, Participant 11 discussed the need of third-party vendors to provide and implement enabling technologies. In this way, external consultants provide tangential support to data-driven initiatives but play a specific, technical-only role in the project: “You may have to engage with some third-party vendors that may provide the necessary hardware or software to accomplish your goal.” A common theme among participants who suggested external consultants was the highly technical roles they fill. Under this model, consultants are able to focus solely on technical integrations and development, a likely core competency of their own business, while leaving culture-defining tasks to internal team members. According to participants, allowing consultants to provide enabling technologies reduces the technical burden on the host organization and provides internal team members with an experienced voice of reason, as well as the space to focus on non-technical aspects of data-driven initiatives.

Participants discussed a variety of skills necessary for members of a business intelligence team to possess. Individuals surveyed often mentioned that leaders should consider these qualities when selecting members for a team. Participants also indicated that members of a team do not need to possess all of the mentioned qualities, but that leaders should strive to represent each skill within a team to some degree. Skills were largely categorized into four dimensions: (a) technical and hard skills, (b) business acumen, (c) soft skills, and (d) leadership. Many of the skills discussed by participants were aligned with those often mentioned by researchers.

Several researchers discussed hard skills necessary for creating a data-driven environment. Chen and Nath (2018) explained that capabilities in technology and in data analysis help unlock a pathway to business intelligence maturity. Organizations should work to build a staff that possesses technological skills so that they may move toward a data-driven culture (Garica-Perez, 2018; Halaweh & El Massry, 2015; Mikalef et al., 2018). Members of a business intelligence team should have an innovative personality and strive to find new, better ways of conducting analysis (Halaweh & El Massry, 2015). Some researchers explain that business intelligence teams should also work to communicate technical details to end users and work to improve decision-makers' technical skills and technological literacy as well (Cekuls, 2015; Jabeen et al., 2016). Despite the status of technical skills as an enabling factor in data-driven decision-making, Halaweh and El Massry (2015) noted that technical implementations are not, by themselves, a satisfactory big data solution.

Possessing business knowledge is a further skill needed among business intelligence team members. Garcia-Perez (2018) mentioned that business acumen helps foster trust in business users. Furthermore, understanding the processes an organization follows in various areas of the business can help analysts and data scientists provide better results (Garcia-Perez, 2018). Being able to understand the application of data in the context of operational and strategic decision-making is a unique skill that must be present in business intelligence teams (Halaweh & El Massry, 2015).

Researchers often discuss the need for business intelligence professionals to possess soft skills. According to Foster et al. (2015), the ability to communicate is a useful tool that analysts can wield to better convey their ideas and findings to decision-makers and, ultimately, earn their trust. Members of a business intelligence team should be able to speak to executive leadership and their internal customers and explain project progress and findings (Garcia-Perez, 2018; Halaweh & El Massry, 2015; Mikalef et al., 2018). Presenting oneself in the proper way can help improve trust in a project, especially when results may be highly technical in nature (Foster et al., 2015).

Finally, many researchers discuss the need to understand tenets of leadership and management. Garcia-Perez (2018) explained that data scientists and analysts should understand organizational processes, be able to explain their purposes, and find ways to improve them. In addition, business intelligence teams should include individuals skilled in project management (Cech et al., 2018; Grubljesic & Jaklic, 2015). This ensures that projects are completed by expected delivery dates, results are positive, and that expectations are managed throughout the business (Cech et al., 2018; Grubljesic & Jaklic, 2015).

Participants discussed a wide range of skills, largely aligning with researchers. In terms of technical, hard capabilities, individuals surveyed frequently mentioned several technological, analytical, mathematical, and statistical qualities that must be represented in business intelligence teams. The first major topic, *IT infrastructure*, was discussed by nine of 18 participants, or 50%. Participant 8 described the ultimate purpose of looking for team members that possess technical qualities, speaking in terms of project objectives: “I think one of the things that would be important would be: What and how do we put together an infrastructure that will allow the development of these databases and these computers that can make these decisions?” Participants agreed that internal resources possessing these qualities would most likely be employed in an information technology role. Participant 14 described the connection between an IT background and the skills necessary to be part of a business intelligence team: “If it’s someone from IT, of course they would have to have the background, at least where they can take the information and know what’s possible, what you can do from the IT side.” Participant 9 discussed the specific roles that would possess these capabilities:

> You need your database people, or whatever data platform you use. You want to have people who understand how to store the data and read the data. Let’s see, so you’ve got your [database administrator], or any role like that.

Some participants explained how IT individuals and those strong in IT infrastructure should apply their skills to a business intelligence team. As a service provider, the IT organization is responsible for creating platforms on which analyses can be developed. Participant 6 stated that IT should understand their platforms and delivery methods and additionally discussed the need for end users to take an active role in defining projects: “We [IT] have the expertise on the back side of all that coming in, and [end users] have the expertise on what they want to do with it and what their endgame is with it.” Participant 5 explained that knowledge and technical capabilities within the technical staff can be applied to the ability of teams to provide tools that enable decision-makers to consume and interpret data:

> The person producing it needs more technical skills than the person using it. They’re going to need to know how to use the tools that pull the data, how to use the tools that are going to create the reports.

The participants who discussed IT infrastructure largely agreed that the skill is necessary as an enabling technology for data-driven solutions. These participants, while still maintaining the importance of other roles, placed a high emphasis on the necessity of IT professionals on business intelligence teams.

Participants overwhelmingly discussed the need for team members to possess the skill of *basic data analysis*. This skill involves the ability to understand data outputs and use data to gain insights. Skills may range from data visualization to statistical modeling. Among participants in the study, 16 of 18, or 89%, explained that this was a necessary skill. Participant 3 stated, “I think you have to have a team that is able to look at the data and understand it.” These skills take a combination of technical knowledge and intuition. In more complex projects, it may be necessary to spread such skills over a number of individual members of a team. Participant 18 described the variety of tasks that must be completed by a team member skilled in data analysis:

> This is where I say you have to have a ninja doing the analysis. Analyzing the data is not just staying true to the data, but it's also being able to manipulate data and turn it around. Like looking through a prism, you turn it one way to catch the light. It has to be somebody that's very well trained in the tools necessary to analyze data, and display it.

Participant 9 called out more advanced visualization or statistical processing, explaining that data can be used for demonstrating trends over time: "I always say if you've got somebody who's got a knowledge of how trends work, of how processes work—because there's a process involved whether it's a direct process or not—that's always a good thing to have." Foreshadowing the necessity of practitioners to understand real-world implications of their analyses, Participant 7 explained the need for business intelligence team members to apply their data analysis skills to business processes and phenomena: "You'd have to be a good analytical thinker, but you'd also have to understand how that relates to real-life situations." Participants explained that once insights and data-driven solutions have been delivered to organizational decision-makers, data analysts should work to transfer knowledge and data analysis skills to the target audience. Participant 5 discussed the need for end users to understand basic data analysis before effectively making decisions using the given datasets: "The skills of the person using the report is going to have to understand what they're seeing, understand the analysis that was built in the report and what it is saying." Finding individuals skilled in data analysis and recruiting them to work on business intelligence teams is another enabling step toward the adoption of data-driven technologies. To become data-driven and improve organizational data maturity, participants explained that the organization must ensure that practitioners possess analytical capabilities.

A small number of participants discussed the need for business intelligence teams to understand *mathematics*. Three of the 18 participants, or 17%, called out the importance of mathematics knowledge due to the often-quantitative nature of data analysis. Participant 3 discussed the necessity behind this quality, calling out the importance of math in the interpretation of data: “May also be, very possible, a math background, with the ability to look at the numbers and interpret.” In this way, analysts can identify the relationships between data points and develop formulas for helping decision-makers understand inputs and outputs of a particular business function. Participant 9 discussed specific fields of mathematics and explained their importance to data analysis: “Probably someone that’s really great at math. […] Algebra and Calculus would be great, but it’s not necessary if they understand how to get to the end logically.” According to this participant, algebraic and relational understandings of phenomena can help business intelligence practitioners convey information to decision-makers using numeric expressions. Though the number of proponents of this skill within the sample set was small, this group found consensus among each other that an understanding of mathematics could be beneficial—though likely not crucial—in business intelligence teams.

A frequent skill mentioned by participants involved *presentation of data*. This presentation includes tasks ranging from visualization of data points to the manner in which analytical results are conveyed. Participants frequently related the presentation of data to actionability of information and consistency of data, hearkening to the concepts of technological trust in data insights. The design of data-driven solutions is an important feature of the work of business intelligence teams that has a great impact on the overall success of such initiatives. Of the 18 participants in the study, 13, or 72%, explained that this is a necessary skill. Participant 2 explained that focusing on the design and layout of analytical solutions can expand the potential audience and increase the impact of the solution:

> It’s easier if you give them a scorecard, or a chart, or a graph, or something that’s prettier to look at and has better visuals. You can speak to a larger audience and make a bigger impact within the organization.

Presentation of data is not limited solely to dashboard design or the marketing angle of solution architecture. In some cases, data presentation is related to the way analysts present themselves to organizational decision-makers. Participant 5 stated that analysts should discuss findings with decision-makers and present findings in a way that projects confidence and builds trust: “You’re going to have to show them the numbers. You’re going to have to do analysis and show them that when we do this, when the numbers show this, and when we make these decisions, this is our result.” Giving attention to the way data are presented to business users, and, from a team design perspective, ensuring that the team possesses the skills necessary to provide adequate data presentations, can help improve the actionability and usefulness of an organization’s data. Participants also noted that appropriate labels of solutions and properly conveying the definition of metrics in the same location as the metrics themselves can improve understanding of data and increase consistency in analyses. Providing this information prevents decision-makers from making assumptions about the underlying data and eroding trust in data sources. Participant 6 addressed this issue, stating that appropriate presentation of data can prevent inconsistencies: “That’s the hardest thing to do. We’ve got to be cautious about how we change the way we actually deliver information to the user so we don’t create those kinds of issues [inconsistencies].” Ensuring the proper presentation of data and delivering solutions in well-designed formats can provide business intelligence teams with an additional level of trust from the organization. According to a majority of participants, teams should look to include individuals skilled in the presentation of data so that information is effectively communicated through visual formats to organizational decision-makers.

When working to solve complex, difficult problems, business intelligence teams may employ *creative problem-solving*, according to participants. Data analyses can sometimes become complicated as a result of missing data, unclear business processes, or a number of other factors. Participants explained that members of business intelligence teams must be able to find creative solutions to difficult problems. This opinion was shared by four of the 18 participants in the study, or 22%. Participant 11 concisely explained, “I want somebody that is kind of a problem-solver.” Participant 1 agreed, stating, “I think that just requires thinking outside the box to see what’s really driving our numbers.” In this way, analysts and data scientists should be able to find creative ways to explain difficult concepts using data, sometimes in the absence of useful data points. Participant 12 affirmed the need to seek out and pursue unique, unexplored paths of data analysis, stating, “I think it has to be a person that is a free thinker, out-of-the-box individual.” Organizational leaders should populate business intelligence teams to some degree with employees who are not afraid to find new ways of completing their work. Such individuals, according to participants, are often useful in eliminating barriers to progress.

A final and often-overlooked technical skill, according to participants, is the ability to provide *documentation* regarding analytical solutions. This may take many forms, though the purpose of documentation remains to provide decision-makers with an explanation of how the solution was designed and how it can be used to guide ongoing and future decision-making. Five of 18 participants, or 28%, called out the need for providing documentation in analytical solutions. According to participants, the ability to provide such a guide is a unique skill that is often forgotten in business intelligence teams. Participant 13, a manager in the organization, explained that documentation is important to helping guide understanding of the information being provided:

> You can give me the reports all day long, but if I don't know how the report was set up and the logic that was behind it and how it's pulling it, how I look at one thing may be entirely different from how the report was set up. So, how I think it should be pulling the data may be totally different. How did we set it up? How did we pull all that? […] You'll have to break it down into layman's terms for me.

Members of a data-driven team should be able to provide documentation in a centralized repository for ongoing reviews and when data consumers need to understand the source of their information. Participant 12 discussed the need for effective communication through documentation regarding the nature of the provided data: "Be able to communicate that in an effective means, whether it be verbally or writing it down with instructions or presentations or whatever."

Although discussed by a relatively low number of participants, building processes around creating documentation for analytical systems is a useful way to build trust in the provided solutions. When selecting members for a data-driven team, leaders should ensure that this skill is represented by a number of individuals.

The second major collection of skills discussed by participants, business acumen, comprises two important abilities of data scientists and analysts. The first of these refers to individuals having a *stake in data*. This refers to an individual's ability to speak to the application of data in their business. In practice, participants stated that this is not a skill acquired by employees over time, but an attribute of their work assignment. Typically, participants explained, employees with a stake in the data are the business stakeholders that are included on the analytics team. Three of the 18 participants in the study, or 17%, discussed the usefulness of included individuals with a stake in the data on business intelligence teams. Largely, participants argued that these members are necessary to help convey the business application of data to other, less business-oriented members of the team. Participant 10, for example, explained: “You need subject matter experts from multiple areas, generally people doing the job or the function at that point in time.” Participant 11 elaborated further on the role of the stakeholder in a business intelligence team, explaining that members possessing this quality are able to identify the important metrics and data points for the organization: “You have to have people that are available to work with that data scientists to create the reports. You’ll need people from the business itself so they can tell you what they think the important measurements are for the business.” Leaders should decide how to introduce the quality of a stakeholder into a data-driven team. The organization may choose to include stakeholders as central members of a team, or, depending on the project charter, include stakeholders as needed. Although mentioned by only a few participants, individuals with a personal stake in data may be a useful inclusion on business intelligence teams.

The second business-centric skill, the ability to *understand application*, was a popular topic among participants. This skill refers to the ability of analysts or data scientists to understand the business impact and meaning behind the data they are studying. This helps individuals know how data relates to the business and how changes may impact different areas of the organization. Although not a technical skill, according to participants, this is a highly important function of business intelligence teams. A strong majority, 15 of 18 participants

(83%), explained the need for including individuals who have a strong understanding of the relationship between data and business functions. Whereas stakeholders have a responsibility to communicate the meaning of data, other team members are charged with listening and understanding how data are applied in the work of others. Participant 6 described the basic components of this skill, focusing on the understanding of processes: “It’s got to be someone that has a good understanding of the business, […] intimate with the processes that you’re trying to work on.” Participant 5 made similar comments, noting that understanding the application of solutions often means knowing the logic behind the presentation of data and how the needs of the business are embedded in the definition: “The skill of the person using the report is going to have to understand what they’re seeing, understand the analysis that was built in the report, and what it is saying.” Understanding the application of data solutions aids business intelligence teams in the accurate development of solutions. Participants also noted that understanding the meaning behind data enables business intelligence professionals to better and more intelligently communicate with key users in operational and strategic business functions. Participant 7 discussed how understanding the nature of underlying data can help to more accurately and effectively elicit the needs of decision-makers while working in conjunction with them:

> We can help communicate upstream, and a lot of times, when they’re trying to explain what they want, they don’t know what they want, and I think [Financial Planning and Analysis] can kind of lead toward what they really want and what their actual outcome is.

This type of support would not be possible without a keen understanding of the stakeholder’s environment. Furthermore, Participant 10 explained that understanding the application of data helps lead to the ability to intuit solutions without conducting a large amount of technical research into a problem:

> He was so ingrained in the business that when he saw data, most of the time he knew what was leading to it. So, when he saw errors, it wasn't like finding a needle in a haystack for him. He pretty much knew intuitively where it was coming from, and that enabled him to go and look and take some foresight and look forward.

If technical capabilities are the enabling factors that allow business intelligence initiatives to proceed, understanding the application of data is the catalyst that helps push technical solutions toward adoption and the next level of accuracy. Participant 17 described the need for a holistic understanding of how the organization operates: "Tool number one would be an understanding of the business, at least a general understanding of the business. Second would be some perspective; they understand how the business works, now give them perspective on how it meshes together." Understanding how the business operates helps provide context to data scientists and analysts. Without this context, analysts cannot effectively or adequately understand the meaning of the data being studied and cannot provide high-quality solutions. Participants emphatically stated that companies should work to ensure members of business intelligence teams have a good understanding of their own business, as well as how data represents the organization.

The third major collection of skills necessary for representation in a business intelligence team, soft skills, refers to the learned emotional intelligence of an individual. The most notable of these skills is the group of *interpersonal skills* that effective change agents must possess. These qualities comprise the behaviors that govern an individual's interactions with others. Conducting oneself in the proper fashion can help effectiveness inside a business intelligence team, as well as communicating project goals and outcomes outside of the team. A vast majority of the participants in the study, 15 of 18 (83%), discussed the need for developing interpersonal skills. Concerning interactions with members of the business intelligence team, participants explained that team organizers should look for individuals who possess qualities of a good team member. According to Participant 11, “You want somebody that’s going to be able to work with a team well.” Participant 6 elaborated that team members must have faith and confidence in both the project goals and the other members of the team: “They’ve all got to understand and believe in each other and the project and what they do and what they bring to the table, in order for everybody to work as a team.” Participant 16 described the collaborative nature of a team and the importance of prioritizing team outcomes over personal goals: “Ability to focus on collective results, not individual results. […] You need to be collaborative. You need to be a team player.” External to the business intelligence group, participants noted that team members must present themselves well. Maintaining a respectable approach in interactions helps provide a welcoming and sincere environment that enables trust between the team and the outside organization. Participant 12 explained that an effective member of a business intelligence team “doesn’t have fear of speaking in front of groups and is able to articulate their ideas.” Participant 5 discussed the importance of interpersonal skills to building relationships with the target audience of a particular business intelligence solution: “They’re going to have to actually have some personal skills to be able to convince and be able to push down those decisions.” Participant 2 corroborated this belief, explaining that the way an individual conducts him- or herself in interactions with decision-makers can be a deciding factor in whether or not end users will place their trust in a solution: “The way you present data as a person to a group or another person is a pretty important part of getting buy-in.” Participants strongly suggested that teams should be comprised of individuals with high emotional intelligence. Business intelligence solutions require a high level of trust and, according to participants, individuals with poor interpersonal skills can undermine the reputation of an otherwise successful implementation. Maintaining a respectful and consistent image throughout the organization benefits both the business intelligence team and their work.

Participants next called out the importance of remaining *open-minded* as a member of a business intelligence team. This indicates that leaders should seek to populate teams, to some degree, with open-minded individuals who are willing to try new and unique approaches to solutions. Remaining open-minded, according to participants, allows the free flow of ideas throughout the team. Five of 18 participants, or 28%, discussed the necessity of remaining open-minded in analytical situations. Participant 18 described the trap that individuals often encounter when performing data analysis:

> The problem we have as operators… we're like deer hunters. Everything we see through the scope is a deer. And if it isn't a deer, we want it to look like a deer. So, we tend to tell pretty little stories and leave out the big part of the narrative that tells a different story.

This illustration demonstrates the bias that can pervade business intelligence solutions if left unchecked. Participant 7 called out the diligence required to maintain open-mindedness and avoid becoming too attached to any one idea: "You've always got to keep an open mind and do the analysis and make sure that the assumptions from the outside parties are reasonable." Though mentioned by a smaller number of participants, leaders would do well to populate teams with open-minded individuals, where possible. In doing so, they create a team that allows the free flow of ideas and is willing to explore new approaches to problem-solving.

Though only mentioned by a single participant, a notable soft skill that was discussed in the study was *inquisitiveness*. One participant, or 6%, noted that members of data-driven teams should be inquisitive and seek to identify and solve new problems. This activity, according to

Participant 10, allows for a steady stream of continuous improvements, and allows teams to explore new potential solutions to difficult problems. Participant 10 stated:

> It starts with inquisitive nature. If you're not inquisitive, you're just punching numbers in a database and you're not even knowing what you're looking for. The whole point is to solve problems. If it was there and everyone was aware of it, it wouldn't be a problem.

Building inquisitiveness, as well as open-mindedness and interpersonal skills, are necessary activities that many participants acknowledged during the study. Strengthening these soft skills helps create trust and teamwork among business intelligence teams. According to participants, when designing team composition, leaders should consider these skills and select candidates who possess the desired soft skills or the capability to adopt such skills.

The final dimension of skills, leadership qualities, refers to the influence individuals have over others. This may also refer to the management traits exhibited by some employees. Participants discussed these qualities infrequently. One participant, Participant 16, discussed *leadership* as a skill, explaining that team developers should select some individuals who exhibit leadership qualities to act as change agents:

> You know, to me, it's all about leadership. And leadership to me is really, really simple. You create the vision for what you want to do or where you want to be. Create the alignment behind it. Then you help foster it along, by delivering or inspecting what people are doing.

Two participants, or 11%, discussed the need for possessing a degree of *project management* skills. Including individuals who are accomplished project managers can help prioritize work, communicate tasks across the organization, and establish momentum necessary to continue progress. Participant 17 explained, "[You] have to be able to put some prioritization in your life."

Furthermore, two participants, or 11%, mentioned the importance of understanding *process management*. Understanding the ways processes interact with data, participants argued, is important for building accurate and useful insights for decision-makers. Participant 18 elaborated, stating, “Probably want them to have some sort of process improvement background as well.”

Participants identified a robust list of desired skills that the host organization seeks when developing business intelligence teams. Possessing one or more of the skill or qualities discussed by participants can help an individual contribute in some meaningful way to the work of a data-driven team. Participants discussed (a) technical skills, (b) business acumen, (c) soft skills, and (d) leadership qualities. Where possible, leaders should strive to represent most of the desired skills in team composition. Table 5 provides an outline of the skills selected by participants, as well as the number of participants who agreed and corroborating research studies.

Table 5

Skills Summary

Skill	Category	Participants	Supporting Researchers
IT infrastructure	Technical/hard	9	Chen & Nath (2018) Halaweh & El Massry (2015) Jabeen et al. (2016)
Basic data analysis	Technical/hard	16	Cekuls (2015) Chen & Nath (2018) Halaweh & El Massry (2015)
Mathematics	Technical/hard	3	—
Presentation of data	Technical/hard	13	Jabeen et al. (2016)
Creative problem-solving	Technical/hard	4	Halaweh & El Massry (2015)
Documentation	Technical/hard	5	—

Stake in data	Business acumen	3	—
Understand application	Business acumen	15	Garcia-Perez (2018)
Interpersonal skills	Soft	15	Foster et al. (2015) Garcia-Perez (2018) Halaweh & El Massry (2015) Mikalef et al. (2018)
Open-mindedness	Soft	5	—
Inquisitiveness	Soft	1	—
Leadership	Leadership	1	Jabeen et al. (2016)
Project management	Leadership	2	Cech et al. (2018) Grubljesic & Jaklic (2015)
Process management	Leadership	2	Garcia-Perez (2018)

Participants largely agreed that team composition was an important consideration when building business intelligence teams. Most participants discussed the superiority of team-driven solutions, though some preferred IT or analyst-driven solutions. Participants identified a diverse set of qualities that should be represented on cross-functional data-driven teams, including (a) technical, (b) business, (c) soft, and (d) leadership skills. Participants also largely agreed that teams should be comprised of a diverse set of individuals from various backgrounds and with varying skillsets. Further supporting statements regarding team design are given in Table 6.

Table 6

Identified Themes and Supporting Statements – Team Design and Population

Identified Theme	Supporting Statements
IT-driven solutions	"I lean on IT to build reports and automate reports so that data is tracked for me."
	"I think it starts with your IT group, but then your IT group… they manage the data and manage the systems that house the data, then they also have to rely on the users to follow the process in terms of entering the data, so that what they're managing is correct."
	"[IT] make[s] sure that data is getting input and output correctly in those systems."
Analyst-driven solutions	"I would say definitely an analyst, whether that be from IT or, well, and you would need an analyst from each of the other departments."
Team-driven solutions	"Everyone employed by the company needs to be involved with it, because a lot of the Operations people are measured… their performance is going to be measured by the data, so they have to be sold on it as well."
	"You're definitely going to need IT, but that's kind of… I'm in IT. But most always, you'll need one of the Finance departments or Accounting. Not all companies have all of the same departments. You have to have the decision-making, whether it be management… always going to be management, but whether it is IT, Accounting, Operations… if people are making decisions that are going to use your data, they need to be included."
	"You've got to have the business side, you've got to have the Finance side, and you've got to have the technical, the IT side for all of it."
	"So, a cross-functional team specifically for us… you would need someone who directly communicates with Operations, whether that be FP&A or someone in IT. So, I would say FP&A is definitely a good source of communication between the two parties."
	"I love the fact that we are hiring FP&A individuals that are analysts. […] I wish that they would bring in more individuals that have an IT background rather than just a Finance background."

	"Yeah, I think that there need to be individuals that can mine and gather the data, and there need to be individuals that can interpret and use the data."
	"Everybody. You can't just start at one level and work down, you can't start at the bottom and work up. Everybody has to be involved with it. It has to be adopted by every business unit."
	"So, you need several IT team members, and some team members also from the business itself."
Skills: IT infrastructure	"You want to have somebody that has some technical skills, somebody that knows SQL, can work in Visual Studio or whatever application we're developing the reports in."
	"Definitely you're going to want your data folks."
	"Something like a data scientist. […] Someone that's potentially a developer-type person."
Skills: basic data analysis	"They really need to understand, in my opinion, basic formula-writing, Excel-type stuff."
	"I think you need to have some type of an accounting background."
	"They don't need to be a programmer or anything, but if they already have a little… some type of… at least need to be able to use Excel, or Microsoft Office."
	"Need to be individuals that can interpret and use the data."
	"You've got to have great analysis skills, should have very good, keen ability to pick out patterns, and things that stand out, things that don't stand out, very detail-oriented because you're… you need to pick out the data that's there, and not just the data but things derive from what you're given, and you've got to have somebody that understands logic, and how to get to a logical end."
	"You'll have to have somebody that is well-versed in data, so you're looking at a data scientist or a data engineer."
	"I think that they have to be willing to, obviously, see the data, analyze it."
	"They should be analytical."
Skills: mathematics	"Obviously, they need to understand math."

Skills: presentation of data	"There are individuals that are really good at just gathering tons and tons of data, and they present it to you, and you're just like, 'This doesn't tell me anything.'"
Skills: creative problem-solving	"The next phase is invention. Inventing something you don't do today."
Skills: documentation	"Some of that falls on the shoulders of IT to be able to tell them in layman's terms what that process is… how they envision the process to function."
	"Attention to detail, you know, as far as record-keeping and ability to stay on task."
Skills: stake in data	"First, they need to be in a role that would benefit from having a data-driven culture."
Skills: understanding application	"The internal team… they're going to know the business. They're going to know how to start getting that data out there."
	"They're familiar with that company and know what's going on."
	"We have the expertise on the back side of all that coming in, and they have the expertise on what they want to do with it and what their endgame is with it."
	"One of the problems that IT individuals have when they come in to Operations is they don't understand the mechanisms and the way that business is done."
	"You've got interpretation. So, an analyst has to understand a piece of the business to be able to look at data to understand how it reacts in the real world or what reactions in the real world could create the data."
	"I think a business analyst is always a nice plus to have because they're a little bit of a liaison between the business side and IT side, so they would have some knowledge of what they would expect a data-driven system to work on the business side of things."
	"I think if either an analyst can go and meet with the business users, and really get involved in their day-to-day operations, and see how either reports or tools that we can provide will help them be more efficient at their job, I would say you would uncover struggles or new processes that they're doing on their own."

	"Know your area of business and how you're running it today. What information are you using to run your business?"
Skills: interpersonal	"They will benefit if they can work well with people."
	"I think the biggest skill in that role is to communicate in a way that bridges the gap between Operations and data."
	"There's got to be a huge amount of teamwork, a huge amount of trust between the team. Collaboration is… you have to be collaborative in that type of setup, because you're pulling information and resources from so many different areas."
	"I think they need to have a teamwork mentality. Good communication skills. I think that communication not only verbally but written because you're going to be seeing a lot of things… you're going to have to be able to convey your thoughts in writing as well."
	"You've got to be somewhat charismatic. […] You have to be able to work well with others."
Skill: open-minded	"I think it needs to be someone that is somewhat open-minded."
Skills: project and process management	"Need to have project skills and process skills."

Subtheme: Culture Transformation. To some extent, all participants in the study discussed the process by which organizations can change their culture. In some respects, participants agreed on the ways organizations can become data-driven, but other topics resulted in inconsistent experiences. Regarding the responsibility for culture, some of those surveyed stated that culture is the responsibility of executive leadership, while others believed that it is a responsibility shared by the entire organization. Participants also discussed what a culture transformation typically comprises, specifically calling out its definition and value-driven nature. When asked to define the process backing the transformation of culture, participants generally identified seven steps that would be ideally observed by the host organization: (a) defining current state, (b) methodically transforming culture, (c) designating an executive sponsor or project champion, (d) consistent messaging, (e) providing training and education, (f) staying the course, and (g) observing continuous improvement.

Participants were, as a group, largely indecisive when discussing the responsibility of transforming culture. Responses generally suggested that executive leadership is responsible for defining and instituting culture or there is a shared ownership of culture that is somewhat facilitated by top management. Researchers often fell into the former group, though some did agree with the latter. According to Calof et al. (2017) and Foster et al. (2015), sponsorship for cultures of data-driven decision-making should occur at the highest level of the organization and take a top-down approach. Bogdan and Lungescu (2018) explained that the business should be structured in a way that facilitates the strategic plans of the organization and allows leadership to push support through the company. Ahmadi et al. (2016) argued that this structure applies to the corporate hierarchy both within IT organizations and the wider business. Calof et al. (2017) suggested that this structure take a highly horizontal approach, explaining that a shallow business, due to the minimization of layers, provides the best change to affect change. Foster et al. (2015) explained that organizational structures should avoid redundancy and that culture transformations should avoid duplicate efforts. Business structure, according to various researchers, may also comprise policies and procedures. According to Ahmadi et al. (2016), top-level management should set policy that supports a data-driven culture. Foster et al. (2015) explained that policy must align with the desired culture; organizations with unaligned policies often encounter difficulty when attempting to transform their culture.

Researchers frequently focus on leader behavior as a catalyst for organizational change or lack thereof. Various studies claim that in an organization driving top-down data-driven culture transformation, leaders should appear excited and highly supportive of culture and initiatives, both in public appearances and in the allocation of resources (Grubljesic & Jaklic, 2015; Halaweh & El Massry, 2015; Mesaros et al., 2016; Mikalef et al., 2018; Thamir & Poulis, 2015; Yeoh & Popovic, 2016). Argenti (2017) explained that often leaders must simply be present. The researcher goes on to explain that if a leader gives the impression of being absent or ambivalent about data-driven cultures, employees will not provide buy-in (Argenti, 2017). According to El Khouly et al. (2017), when affecting culture, leaders should adopt the proper form of leadership; the researchers argue that this style should not be democratic in nature. Finally, Farrell (2018) encouraged leaders to lead by example and to be consistent with their messaging to individuals throughout the business.

Eight of the 18 participants in the study, or 44%, at some stage of the interview discussed the need for *top-down culture transformations*. Of the eight participants, three, or 38%, also discussed shared responsibility of culture transformations. These eight participants represented all of the surveyed areas of the organization, including Operations (three participants), Finance (two), IT (two), and executive leadership (one). Participants were often to the point when taking the top-down approach. Participant 7 clearly stated, “I think the culture starts with the executives and goes down.” Participant 3 described a top-down approach to culture transformation, explaining that leaders should ensure that the managers in the next level provide a united front and continue to push values down one level at a time:

> It needs to be presented to everybody, not necessarily the same way, but it needs to be consistent from the top down, and management needs to ensure that their people are being consistent with the values, and their people, and their people, all the way through the organization.

This approach requires long-term consistency in messaging and is highly dependent on the open-mindedness of leaders at each of the top levels in the organization. Participant 13, consistent with various aforementioned researchers, described the necessary eagerness of leaders when backing a culture transformation: “You have to lead your team on how they can achieve those goals. And when they see that your management is backing them and truly rooting for them and cheering them on to be successful.” Participant 4 explained that the behavior of executive leadership must be in alignment with the stated goals of a culture transformation: “It includes the chairman of the board, board members, everybody… that culture starts with them. If they’re trying to create a certain culture, they have to walk the walk, not just talk the talk.” The suggestions observed by participants in the host organization largely followed the guidance set forth by researchers. Participants discussed the need for flow of principles to each level of the business, the support and presence of top leadership, and the behavior and decision-making of executives in the organization.

A second group of participants instead discussed the possibility of adopting a *common responsibility for culture*. This approach is also backed by literature, though to a smaller degree and somewhat more indirectly. Knapp (2016) discussed the role of teamwork in an organization and that common ownership creates engaged employees and facilitates cultural transformation. Calof et al. (2017) and Foster et al. (2015) each discussed the need for business intelligence teams to act as change agents and to seize momentum where possible to transform culture. Seven of the 18 participants, or 39%, discussed the need for a common responsibility for culture; this was only one less participant than the top-down approach. Of the participants who suggested a shared responsibility, three (43%) also discussed top-down approaches. One participant represented Operations, with two participants each from Finance, IT, and executive leadership.

Participant 2 explained that companies should take the common responsibility approach, while acknowledging that many companies take a top-down stance: “I think that you have to get buy-in from all levels, not just top-down, which is what I think a lot of companies try to do.” The host organization conducts yearly reviews to elicit company values from all employees, which forms much of the basis of the desired culture. Participant 4 addresses this procedure, explaining that executives facilitate the definition of culture but that culture’s true characterization is set by all individuals:

> I think what we did here by letting our team members pick their values, was a good thing, a smart thing, because that way… I’ve always believed that you have to include your whole organization when it comes to your culture. You have to get that feedback on what is important to them, because when you’re at a company and you’ve got multiple types of people and types of personalities, you might have different values among those personalities.

Participants who believe in a common responsibility for culture were quick to identify change coalitions and change agents who are responsible for the messaging and propaganda in support of a culture transformation throughout the organization. Foreshadowing the need for change coalitions, Participant 9 stated: “[You need] everybody. You can’t just start at one level and work down. You can’t start at the bottom and work up. Everybody has to be involved with it. It has to be adopted by every business unit.” Participant 8, an executive leader, discussed the concept of a change coalition, explaining that this team is tasked with successfully modifying culture in the business:

> If they were to create what they refer to as a change coalition, if they were to… individuals that push and want there to be change. And it doesn’t have to be just 15 or 16

> individuals in the company, if can be the whole company that makes changes. And you can change culture and make it stick.

The change coalition works to support and push changes in the organization and helps project a sort of grassroots approach to culture transformation. This utilizes influential individuals in strategic parts of the business to reach the entire organization. Participant 16 explained the coalition in greater detail, explaining that it can consist of managers and workers but that it specifically does not include executives:

> The only way that you can get alignment is by getting a guiding coalition together. I don't mean your executive team. I mean the people that are going to drive adoption throughout the organization. Have to have somebody other than the executive team pushing it forward, or it won't go anywhere. And those are the people who typically have influence across the organization. Sometimes they're your mid-level managers, sometimes they're just your worker bees that are strongly data-driven.

Belief that an organization should push ownership to all individuals does not necessarily indicate a hands-off approach from executive leaders. Under this model, leaders are still responsible for facilitating the change and making final decisions. Participants explained that although values may be sourced from employees and that a change coalition might work to affect change, these processes were developed and carefully built by leadership who does so to promote change using the most effective resources available.

According to participants, an early step in transforming culture is clearly defining the desired end result. Dimitrova (2018) suggested that culture should be carefully defined on top of organizational values. Researchers often find that culture should also be aligned with a company's strategic goals (Akaegbu & Usoro, 2017; Hassert, 2018; Mehdi et al., 2017; Stacho et al., 2017). Once organizations understand their desired principles and build a culture and a strategy to reach the culture, they may begin executing the implementation (Argenti, 2017; Farrell, 2018; Knapp, 2016; Lewis, 2019; Stacho et al., 2017). The appropriate culture will help drive employees toward behaviors that support the goals of the business (Stacho et al., 2017). Five participants of 18 (28%) discussed the need for business to *define culture* before beginning a transformation endeavor. Participant 6 stated that for businesses to reach their desired organizational culture, it must first be defined: "I think the biggest thing about a culture is, it's going to be defined, what you're wanting to do and the things you're wanting the new culture to be, in order to get there." Similarly, Participant 16 explained that a desired culture must clearly be defined, which enables businesses to begin socializing and recruiting members of the change coalition or wider organization: "To me, it's establishing clarity up front about what you're trying to achieve, and then you get alignment." Participants did not specify methodologies that might be used for selecting attributes of a culture that align with goals, as recommended by researchers. However, participants discussed the host organization's methodology for defining culture. Participant 2 described the process, stating, "Everyone participated in making the culture or choosing a new culture." This democratic method of culture definition is not recommended by researchers (El Khouly et al., 2017) and does not guarantee alignment with organizational goals.

Researchers and participants both elaborated and reiterated that culture transformations should be value-driven. According to Aleong (2018), organizational culture is the foundation for identity, values, processes, and procedures in a company. This is in opposition to many other researchers who state that values drive culture, as Aleong (2018) instead claimed that values are informed by culture. Dimitrova (2018) discussed values as one of the three principles upon which a business is built. Aragona and De Rosa (2018) showed that organizational processes should be connected to values as well. Two participants of the 18 in the study, or 11%, discussed the need for *value-driven culture transformations*. Each of these participants was highly passionate about the concept. Participant 8 spoke to the way individual employees can be influenced through their values and making sure individuals understand the difference between values and priorities: “I know how to influence individuals to change their cultures, and a lot of it has to do with, and starts out with, values and a mission statement.” Participant 10 explained that data-driven cultures in particular are highly reliant upon trust and that values such as trust and integrity are critical prerequisites to achieving higher rates of data maturity:

> You can have all the integrity in the world, but until somebody trusts you, that’s devalued significantly. It all forms around that to me and develops from there on out. And once you have that trust, you can combat and progress on a lot of fronts with that core base.

Ensuring that a defined desired culture is rooted in values is essential to creating a foundation that leaders and change coalitions can build upon. Though only discussed by a small number of participants, value-driven culture transformation appeared to be an important component in culture design within the host organization.

According to participants, for a specifically data-driven culture, businesses should strive to embed data and technology into organizational processes. Doing so forces data-driven decision-making to become part of the culture of the company. Several researchers back this stance, explaining that embedding data into employee work helps weave data-driven decision-making processes into the fabric of the organization (Aragona & De Rosa, 2018; Cech et al., 2018; Lawler & Joseph, 2017). A goal of any data-driven culture transformation should be to achieve data embeddedness to help drive data maturity (Lawler & Joseph, 2017). This can be achieved through repetition and consistency (Aragona & De Rosa, 2018; Cech et al., 2018;

Farrell, 2018; Lawler & Joseph, 2017; Lewis, 2019). Four of the 18 participants in the study, or 22%, explained that the *embeddedness of data* should be considered when transforming culture. Participant 9, for example, stated that data are an asset and that it becomes part of decision-makers' standard decision-making processes:

> I think really that data becomes our strength at that point for helping our business folks make those decisions. They can lean on us for that. Even though it may not always seem like that, they do lean on us for helping guide them.

Just as researchers described data processes becoming embedded in the fabric of the organization, Participant 16 described the ability of data to burrow its way into the building blocks of the business:

> It becomes contagious. And it becomes part of our DNA. This is how we do things here. This is how we document processes at USA Truck. This is how we score ourselves every day. This is how we set ourselves up every year to align IT with the greater business objectives. This is how we do one-on-ones here. This is how we conduct our daily stand-up meetings. It just becomes… this is our DNA.

An objective of any data-driven culture should be that data become embedded in business processes and codified into the organization. This helps maintain a data-driven culture long after implementation and, in some cases, embeddedness of data can have a positive or negative effect on the ability to change culture.

To successfully transform organizational culture, and specifically into a data-driven culture, participants collectively identified seven unique steps: (a) define current state, (b) be methodical, (c) identify an executive sponsor, (d) be consistent, (e) provide training, (f) stay the course, and (g) adopt continuous improvement practices. Researchers identified a similar collection of habits that may help organizations become data-driven. The first step identified by participants was to *define current state*. Cech et al. (2018) explained that businesses should work to understand their current decision-making environment before trying to affect change. Villamarin-Garcia and Diaz-Pinzon (2017) elaborated that this evaluation must validate that conditions for change are favorable. In evaluating the current state and future state, Farrell (2018) explained that the goal should be to understand gaps between the two and identify ways to bridge these gaps. Farrell (2018) also explained that leaders should work with individuals in the organization to understand the current state and gaps. Finally, researchers explain that leaders should work to identify a path toward the desired culture by closing the identified gaps (Farrell, 2018; Stacho et al., 2017). Of the 18 participants in the study, seven, or 39%, identified the importance of defining current state. Participant 5 explicitly stated that this is the first step in transforming culture, stating, “First, you have to clearly define your previous state.” Participant 6 elaborated that the current state must be compared to the desired future outcome:

> If you don’t really know what your current culture is and what the culture you’re wanting to get to is, I think that’s probably the biggest thing you’ve got to… you’ve got to understand where you’re at and where you’re wanting to go.

Participant 12 agreed and compared understanding current state to an individual knowing the amount of money in his or her bank account:

> You make decisions on a day-in and day-out basis based on the data. If I look at my bank account today and say that I’ve got X amount of dollars, I’m going to make a decision that either I’ve got the money to spend for this, or I don’t. If you don’t look at your bank account, odds are at the end of the week you’re probably not going to have a lot of money in your account.

Applying the concept to data maturity, Participant 8 included the need to look back on an organization's history when understanding the current state: "Identifying as a data scientist where you were, where you're going, and where you're at right now are critical." Just as researchers claimed that an organization's current state must be understood, participants frequently discussed the need for knowing their own company's existing environment. In this way, the host organization can understand gaps between the current and desired future states and begin to eliminate discrepancies.

Participants stated that after identifying the current and future states and the gaps that exist between them, change agents must identify and execute on concrete steps to reach their desired end result. This takes the form of a *methodical transformation of culture*. This is supported by researchers as well. Cech et al. (2018) explained that change coalitions create culture through consistent execution of smaller tasks; organizations become more mature with each successive task. This slow and often tedious methodology improves an organization's maturity immensely over a long period of time (Cech et al., 2018). Farrell (2018) and Lewis (2019) cautioned that culture should be applied consistently and repetitively for maximum effectiveness. Four participants of the 18 in the study, or 22%, called attention to the need for methodical transformation of culture. Participants noted the necessity of planning intermediate steps between current and future state. Participant 11 explained, "You kind of need to have a roadmap of what you're trying to accomplish." Similarly, Participant 1 discussed the way the host organization built their desired culture, specifically calling out the methodical planning and intermediate steps that were required: "So, I think over time, we've been able to build that culture into the environment we want to see, but we had to take all those steps in between."

Transforming culture, and in particular, making an organization data-driven, requires a disciplined approach to following a methodical plan. Developing intermediate steps and taking concrete steps to transform culture one task at a time, according to participants, is an essential second step in building the desired environment.

A critical step in transforming culture, participants stated, is obtaining sponsorship and championship from executive leadership. Gaining the support of an *executive sponsor* allows data-driven cultures to proceed, while a lack of executive support often undermines projects and creates the wrong effect on organizational culture. Researchers overwhelmingly back this claim, often showing that executive leaders should (a) be supportive, (b) be enthusiastic, and (c) be present and engaged. Mesaros et al. (2016) explained that strong executive champions facilitate the free movement of initiatives throughout the business. The support of top management for the transformation of culture is considered by many researchers to be essential for an initiative’s success (Halaweh & El Massry, 2015; Thamir & Poulis, 2015). Some researchers suggest that this support should be formalized through executive sponsorship of an official project (Calof et al., 2017; Foster et al., 2015). Furthermore, leaders can simultaneously signal their support for a culture transformation and provide the initiative with resources by allocating investments into such projects (Mikalef et al., 2018).

According to participants and researchers, executive sponsorship also requires that leaders be enthusiastic about data-driven initiatives. This enthusiasm permeates throughout the organization and serves as a catalyst for a culture transformation. Grubljesic and Jaklic (2015) described the need for public executive support, going further to state that this support must be prominent and notable. Chen and Nath (2018) showed that despite public support, private executive opinions of technology and IT groups can positively or negatively impact a data-driven culture. Executive leaders must be careful to not undermine the progress of the change coalition while working to transform a culture.

Importantly, executives must provide support and be enthusiastic about a data-driven culture; they must also be present and lead by example. Argenti (2017) explained that front-line and mid-level employees look to leadership for guidance and that absent leaders are ineffective in leading by example. Farrell (2018) affirmed this claim, explaining that leaders should demonstrate willingness to adopt data-driven technologies. Morton et al. (2018) found that one of the leading success factors in a culture transformation is the extent to which executives are involved. Yeoh and Popovic (2016) explained that top-level adoption of technologies cascades down in an organization, hearkening to the belief that culture transformations should occur in a top-down fashion.

When discussing the necessity of an executive sponsor or project champion, 10 of 18 participants, or 56%, agreed with researchers and argued that executive buy-in is critical for transforming culture. Participant 16 discussed the importance of leadership's public stance toward the use of data and that leaders should apply data in various dimensions:

> Then I would say the other component of that is tone at the top. Is your leadership placing an emphasis on the importance of data? Is your leadership using data for all kinds of different things, like business insights, governance, performance, things like that?

This tone refers to the attitudes that leaders display toward data usefulness and correctness. Participant 10 explained that change coalitions should ensure that leadership is a stakeholder in the transformation process to provide leaders a greater platform to discuss goals:

> And then, support the project. If the business leader doesn't support the work then it's going to fall flat. So, they have to be bought in, they have to be a stakeholder. They have to be supportive, let the project move where there are as few hurdles as possible.

Leaders should take an active role in engaging with other members of the organization to support the transformation initiative. Participant 18 explained that a transformation is most effective when executive leadership is knowledgeable and supportive: "By supporting their ideas throughout the organization. Validate them. Support them. I think that gives them everything they need to affect change." Participant 6 warned against the power of negativity from executive management, stating that negative, public feedback can be detrimental to a project:

> So, you've got to have good buy-in, especially at the executive level. Because anybody with any kind of power at all doesn't believe in it, talks bad about it, then it just propagates all the way through, then nobody believes it.

According to participants, leaders wield tremendous power with regard to support. Leaders who support projects enable change coalitions to affect culture throughout the business, though leaders who denounce a transformation risk causing project failure. Leaders should ensure they remain supportive and enthusiastic of data initiatives so that projects may proceed uninhibited.

As a fourth stage of culture transformation, participants explained that the organization must provide a degree of stability. For change coalitions and leaders to best institute a new culture, participants discussed the need for *consistent messaging* from leaders and change agents. Researchers generally agree; Farrell (2018) and Lewis (2019) explained that consistency and repetition are necessary for ensuring all employees are acting as a cohesive group. Consistency, according to Cech et al. (2018), allows culture to become embedded in the organization and results in a strong environment of data-driven decision-making. Farrell (2018) and Lewis (2019) discussed the necessity of culture promotion to occur across the entire horizontal organizational hierarchy and that this promotion should be applied with consistency and repetitiveness. Foster et al. (2015) suggested formalizing processes and best practices that support consistency and allows for the growth of a data-driven culture. Of the 18 surveyed individuals, seven, or 39% of participants, called out the need for consistent messaging. Participant 4 explained that consistency can be regulated through policies and procedures and through ensuring the appropriate enforcement of these procedures: “I think it starts and ends with having those processes in place, and documenting those processes, and obviously making sure those processes are always followed. If the processes are always being followed, that culture kind of just continues.” Building a consistent culture requires a degree of organizational stability and solidification of structures. Participant 7 explained a professional relationship with a particular executive leader who consistently pushed for data-driven decision-making and the results of these efforts:

> I’ve definitely seen the data maturity move with how hard we’ve pushed it over time, it definitely comes down from [an executive leader], and he’s definitely to the point where he won’t accept anything and he’s not happy with anything until he sees the data behind it.

This stability requires long-term stability in organizational goals and, often, leadership tenure. Participant 12, a long-term member of the organization, described experiences with leaders over time and a specific tumultuous period in company history:

> I would say that consistency is a huge thing. That’s the thing that over the years we haven’t necessarily had at USA Truck. There’s been a lot of changes in the leadership. You have a lot of different people, they come in, they have a higher value placed on one

> thing, then another thing, or they want to put their own little twist on it. So, being consistent, not necessarily having a lot of turnover, helps in your overall company culture, because turnover breeds uncertainty.

Remaining consistent in messaging allows organizations to create a stable environment where a new desired culture can breed and take root. Participants and researchers agreed that stability and repetition help employees within an organization understand goals and create a cohesive group where teamwork and collaboration thrive.

A fifth tenet of a data-driven culture transformation, as specified by a number of participants, is *training and education*. Providing employees with training in data-driven decision-making procedures and technologies allows organizations to further their foray into data maturity. Ahmadi et al. (2016) explained that organizations should be fluent in data-driven technologies and application to best adopt a culture of data-driven decision-making. Furthermore, the researchers assert that modern organizations frequently are ill-equipped in organizational knowledge to successfully understand technological solutions (Ahmadi et al., 2016). Kimble and Milolidakis (2015) concurred, explaining that leaders and employees often subscribe to a number of popular myths regarding business intelligence technologies. Researchers therefore encourage organizations to invest in resources that can provide members of an organization with the training necessary to understand data-driven technologies (Foster et al., 2015). It is the responsibility of top-level management to invest in training for their employees (Grubljesic & Jaklic, 2015; Halaweh & El Massry, 2015; Mesaros et al., 2016; Mikalef et al., 2018; Yeoh & Popovic, 2016). Education for employees helps workers to better understand how to interpret and apply results of data analyses, which leads to better decision-making and ultimately firm performance (Basic & Aleksic, 2018). A basic understanding of business intelligence principles also allows leaders to more effectively manage the day-to-day operations of data-driven initiatives, even when they are not involved in decision-making at the operational level (de Saint Laurent, 2018). A culture of learning, according to Kimble and Milolidakis (2015) and particularly with regard to data-driven decision-making, supports more informed choices and allows operators to better support the strategic objectives of the organization. Many researchers support the need for education regarding fact-based decision-making (Cekuls, 2015; Garcia-Perez, 2018; Halaweh & El Massry, 2015; Mikalef et al., 2018).

Of the 18 respondents in the study, 10 participants, or 56%, discussed the notion of training and education in the midst of a culture transformation. Several participants discussed the need to educate employees in the principles of statistics and data-driven decision-making, as well as the organizational knowledge necessary to be an effective decision-maker. Participant 10 explained that training should be developed to help guide decision-making toward choices that benefit the company:

> I think it starts with education. So, we're in an industry where you have a lot of… if you take our entire employee base, you take drivers, terminal employees, brokers, all the way through… there are a lot of people there that have never experienced or never been through education of data. They've never been through a statistics class in college. They've never been taught how it can be used to your advantage and how it can be used to develop a business. So, you've got to teach them first.

Participant 2 discussed the need for individuals to be instructed in the ways they can retrieve information within the organization, stating, "People who have the questions need to be taught where to go to ask the right questions." Participant 6 agreed, explaining that employees should be coached in the specific ways data can be retrieved within the host organization: "That's probably the biggest thing, if we're going to have a data-driven culture, people have to understand… this is where I get my information. This is how I get my information. That's how it's done." Some participants proposed a forward-looking comprehensive training program. Participant 3 explained that a percentage of training should be designed to educate employees in existing systems, while additional training should be provided to help prepare for future improvements:

> I think there's a level of training that needs to be done, whether that training is to maintain current or one to two years down the road, or maybe dedicate analysts that are looking one to two years down the road and they're keeping the other analysts going with where they're currently at, but ultimately I think training is the only way to stay on top of that. Continual education.

Participant 8 corroborated the need for continuous education, explaining past experiences with leaders beginning to drop investments for data-driven initiatives: "You've got to reeducate and reidentify what the numbers of it are and show it in a manner that prevents them from denying the system." Training and education allow businesses to provide their employees with the knowledge necessary to effectively use their tools. Researchers and participants in the study found similar results, with participants consistently stating that increased knowledge improves effective usage of tools and in high-level management of data-driven projects.

As a sixth component of a data-driven culture transformation, participants identified *staying the course*, indicating that leaders should not be quick to move on to other initiatives or abandon projects due to short-term losses or failures. Participants explained that data-driven initiatives are often long-term investments that can take an extended period of time to yield significant results. Researchers agree that leaders should practice a reasonable degree of patience with regard to data-driven initiatives. Farrell (2018) and Lewis (2019) described the long-term nature of data-driven investments and explain that consistency with regard to organizational goals is necessary to build a data-driven environment. Various researchers explain that businesses should protect their culture and think of long-term ramifications of short-sighted deviations in policy (Argenti, 2017; Farrell, 2018; Knapp, 2016; Lewis, 2019; Stacho et al., 2017). Farrell (2018) explained that surveys and interviews with members of the organization can be taken periodically to measure culture and demonstrate intangible and frequently immeasurable improvements in the organization; such a tactic may help ensure the extension of the investment.

Some 10 participants of the 18 recruited to the study, or 56%, explained that business should be more focused on long-term maintenance of culture, when possible. Participants acknowledged the imperfections and inexactness of data-driven decision-making, though stressed that the organization should not be quick to react to short-term failures. Participant 4 confirmed that data-driven models may be imperfect but generally contribute to better organizational decision-making: “I think some of the risks are, obviously, this is going to be a trial and error type thing. So, you’re going to have errors. You’re going to have mistakes when you’re trying to implement your processes.” Participant 15, a leader within the organization, admitted that day-to-day, short-term tasks and decisions that result in small but quick gains often distract from long-term improvements with higher returns:

> Unfortunately, a lot of times as business owners we get distracted with actually doing the day-to-day tasks of the business, and so those projects tend to fall by the wayside because you don’t see an immediate impact to the business, generally speaking.

Participant 8 referenced an occurrence in another organization in which a data-driven initiative was discontinued and business intelligence personnel fought for its reinstatement: “They actually had made the decision to discontinue using data, and discontinue using the models to be able to affect those specific areas of business. And we as the […] department had to go back out and reeducate them.” Leaders and change agents should understand that data-driven initiatives are not short-term projects with immediate returns. To a reasonable degree, and in the absence of a breach of confidence in business intelligence personnel, leaders should be willing to allow business intelligence teams to work to provide large returns, long-term.

The final stage of culture transformation, as defined by participants, is a phase of *continuous improvement*. Participants explained that post-implementation, organizations should work to make incremental improvements over time to protect the hard-fought culture and to continue demonstrating the usefulness of data-driven initiatives. This is backed by Benmoussa et al. (2018), who explain that continuous improvement in data-driven initiatives is key to survival. Of the 18 participants in the study, 14, or 78%, discussed the need for continuous improvement. Participant 6 acknowledged the imperfections of data-driven decision-making and explained that a continuous improvement model would help protect the organization: “It’s a learning process and how it works and how it works for you because nobody is going to get it right the first time, and it’s going to mature over time.” Participants also described the usefulness of continuous improvement in maintaining culture and in taking the organization to new levels of success. Participant 11 explained that data analysts and business intelligence teams should be watchful for opportunities to make further improvements and contributions:

> You constantly, I think you want to be driving it forward. So, if you’ve got a data-driven culture already, and your business is bought into it, they’re accepting of the numbers, you

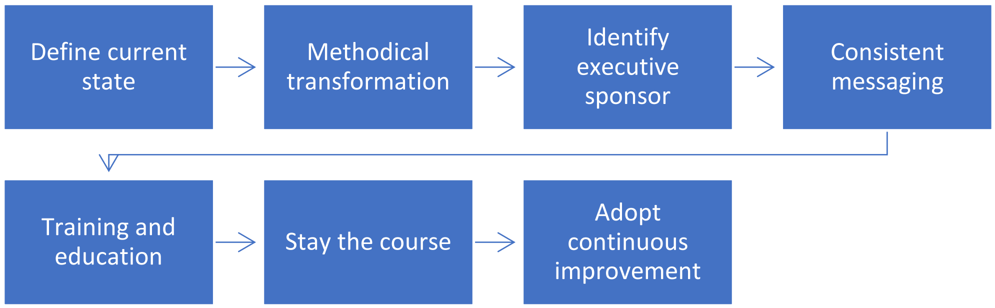
> want to continue to look for additional ways that data can be used to drive business forward. How else can we use this to make our data more efficient and more effective?

In creating additional opportunities to improve data-driven decision-making, continuous improvement efforts affect firm performance. Participant 16 discussed this relationship, explaining that continuous improvement is useful in bettering the organization: “If you’re able to use that data to feed continuous improvement efforts, that contributes to your ability to improve performance overall.” Participant 13 described the effect of an appropriate culture, explaining that people eventually become self-sufficient and begin continuous improvement efforts through their own initiative: “They’re just not satisfied with hitting the results, now what can we do to get even better than this?” Continuous improvement efforts, as the final stage of a culture transformation, allow organizations to frequently review procedures and results, with the intention of making incremental improvements over time. These improvements contribute to the long-term viability of data-driven initiatives and serve to make gains in the face of ever-increasing goals.

To create a data-driven culture, change coalitions must observe seven phases or aspects of culture transformation. According to participants, these dimensions include (a) defining the current state of the organization, (b) being methodical about identifying and executing on intermediate steps, (c) designating executive sponsorship, (d) maintaining a consistent and repetitive message, (e) providing education and training, (f) focusing on long-term goals, and (g) adopting continuous improvement. The process behind an effective culture transformation within the host organization, according to participants, is provided in Figure 4.

Figure 4

Cultural Transformation Process



Discussions with participants revealed differing accounts of who is responsible for the transformation of culture within an organization. Some participants left the responsibility with executive leadership, while others suggested that change in a business is also the obligation of a change coalition and, ultimately, the entire organization. Most participants discussed the need for, at a minimum, executive involvement. Participants explained the process by which organizations should define their culture, with several focusing on organizational values and the necessary embeddedness of data-driven decision-making. Regarding the transformation of culture, participants defined seven phases, ranging from defining the current state to reaching a point of continuous improvement. Supporting statements for the selected themes regarding culture transformation are provided in Table 7.

Table 7

Identified Themes and Supporting Statements – Culture Transformation

Identified Theme	Supporting Statements
Top-down responsibility for culture	"I think first you have to have the buy-in of leadership. Management has to get behind the idea 100%, and then you need to start sharing that information with the organization, the people actually doing the work." "It has to start with leadership to change a culture."

	"Culture is something that starts at the top and kind of works its way down."
	"So, I really think it's when the next level down, your first level or second level management, when they take the ball and start running with it. And it doesn't… it no longer needs to be suggested or driven at the executive level. That's how you know change has come into effect. And I'm starting to see signs of that all over the place."
	"So, what jumps into my mind right away is buy-in from executive level. We're doing [a project]. I've been a member of that since we started it, and there is top-down involvement and backing leadership in that."
Common responsibility for culture	"You have to get everybody involved and everybody is part of that process and that's how that culture gets redistributed throughout the organization."
	"I feel like you've got buy-in from a multitude of locations, and top-down, that's a good way, in my opinion, to change a culture."
Defining culture	"If you don't really know what your current culture is and what the culture you're wanting to get to is, I think that's probably the biggest thing you've got to… you've got to understand where you're at and where you're wanting to."
	"First we have to identify what that culture is."
Embeddedness of data	"It needs to integrate with our current products that we use day in and day out."
Value-driven culture transformation	"It's got to be something that is a true culture or value that you're uncompromising on."
Define current state	"I think you'd have to look at, when you started, let's say if you're not in a data-driven culture currently, and you're planning on trying to get there, you need to take a look at I guess how the business is current performing, and the processes and everything that are in place currently, and then every three months, six months, every milestone, whatever those are set to be, you go back and you evaluate that, and you see how you've grown or progressed since that previous milestone."
Executive sponsor	"Number one, they're going to have to see the value in it, and understand… too many times, when a company starts to do poorly, IT is usually one of the first places they start cutting heads."

	"Internally, I would say that you've got to have the right executive and management team that's willing to pursue those products that are going to enhance your capabilities." "I think if the business leader adopts that mentality, and reinforces it with their team, then that should clear a path for the IT leader or the project manager to give the information they need." "It's got to be your executive team has to believe in it, because they have to sponsor it, and they have to condone the resources for it. So, that's absolutely key." "I think you need somebody, a project champion."
Consistent messaging	"So, as long as everybody is buying in and believing that process and following it, that will allow you to maintain that consistency, that culture of being data-driven."
Training and education	"And if they don't it's probably best to get somebody from the outside to teach them how to do that." "We had to actually teach classes on how to understand the data." "And through training, I think would be one of the best things." "I think your projects, whether small or large, should always be supported by data, and it just becomes how we do things, and that's how you hold onto it. It's a training issue."
Staying the course	"I think the downside is, sometimes you don't realize what actually drives your company until you do the project and you want to go data-driven and it's a good thing you find out what's actually making the change, but sometimes it takes some big changes that people don't like." "The problem happens when you've always done it, and you don't realize what kind of stuff it is, and people start gradually going away from spending money on it, keeping resources available to do it, and then all of a sudden you don't have someone to manage it if it gets out of kilter, it goes away, or somebody tries to… it goes away, something changes, or whatever. By then it's too late. You're back to floundering again and trying to get back to where you were." "I think the quickest way to lose it is to stop investing in it." "The risks can be… sometimes it can take a while."

	"It can be exciting when you get it out of the box, and then it sits on a shelf somewhere and then you don't use it."
	"You have to hold on to your governance process. It can't become a free-for-all. It wasn't just a one-and-done, like when you go into maintenance mode… that's when your process is more important than ever. And then there's that governance. And I think, maintain it. Process, process, process. In maintenance mode, it's all about process. Maintenance to me includes submission of changes, submission of errors, submission of new ideas that maybe we're not doing right now."
Continuous improvement	"Once we get scorecards done and the basics that people need to look at to be successful, I think that's when you start opening up more time in your day-to-day, where you have a system that does all that work, then all your analytical types of people can dig into even more problems."
	"I think once you set those processes and that culture of accountability and continue this process then I think over time you'll start to yield results."
	"You've got to invest in it, and keep on going down that road where, 'Hey, we want to be in the leading edge of technology and the leading edge of solutions. We want to be the best at what we do and how we do it.' Then you've got to stop and reevaluate your current situation and see what the possibilities are."
	"Making sure people have their checks and balances and follow their processes and are actually using it, using whatever it is we've done with that data on a regular basis and if there are issues we report them quickly, and if there are things working correctly we report them as well, so we kind of create that… we actually do what we said we were going to do."
	"If you've completed all the steps until then, I think you could almost say that that's getting into a mature organization that's trying to… you could go… standing up data, using data to make a better company, then the next phase is invention. Inventing something you don't do today. Going back to the bar chart and revenue and expense, growing the width instead of the height to cover a larger area. Solving customers' problems they don't even know they have."
	"I think we need to make sure from an IT standpoint that we're always following up. And especially trying to get feedback and trying to improve on it, and deal with it."

> "The ability to have, to draw insights from the data, so the visualization aspect of it, I would say. Giving people a sense of empowerment to be able to look at the data in ways that they gain insights and are able to take actions for continuous improvement."
>
> "I think the key to it is continue setting new goals."

Theme 3: Design of Work Processes

A major theme identified by participants was that of process design for decision-makers and decision support personnel in the organization. Participants discussed a variety of topics that indicated a strong preference for designing standard work processes both around the production and consumption of data-driven platforms. Major components of this theme included decision-making processes relating to general data usage and system usage. Additionally, data administration topics were addressed, including (a) goal-setting and project prioritization, (b) team management, (c) project management, (d) data governance, and (e) evaluating success. Participants largely found that goal-setting should largely be a collaborative effort between leadership committees and business intelligence team members. Participants also recommended the use of well-developed data governance processes to oversee the development and delivery of data-driven solutions. Finally, participants discussed the ways businesses can measure the success of data-driven initiatives, finding that identifying related organizational metrics can serve as a measurable indicator of a data-driven culture.

Subtheme: General Decision-Making Processes. The heart of a culture of data-driven decision-making is, ultimately, modifying the core processes by which individuals make choices. The root of this strikes the central biological processes that occur when a human being is presented with a decision. Therefore, to transform a culture into one of data-driven decision-making requires a cursory understanding of biological decision-making processes. Organizations must also consider the way data interacts with these processes and acts as a substitution or supplement.

All employees in an organization are presented with many decision points directly related to their job function (Cronje et al., 2017; Dezfouli et al., 2019). For most employees, decisions are high in volume but limited in scope; these operational decisions are largely low-impact but aggregate to a highly influential collection (Basic & Aleksic, 2018). Researchers describe various factors that can contribute to a particular choice, including (a) political landscape, (b) economic burden, (c) social pressure, (d) opportunities in technology, (e) environmental issues, and (f) regulatory compliance (Espinoza et al., 2019). The decision-making process, according to Abdallah et al. (2019), often involves four distinct steps: (a) receiving input, (b) processing inputs, (c) prioritizing choices, and (d) selecting an option. Often, decisions are influenced by emotions or cognitive biases (Bucurean, 2018; Chong et al., 2018; Montibeller & Winterfeldt, 2015; Otuteye & Siddiquee, 2015; Paraboni et al., 2019). Understanding the ways micro-decisions affect the strategic direction of an organization is necessary for change agents to drive decision-making alignment with the strategic goals of the company (Basic & Aleksic, 2018; Mendes et al., 2018; Nikeriasova et al., 2016; Schneckenberg et al., 2017; Weiner et al., 2015).

Nine of the 18 participants in the study, or 50%, discussed the need for understanding *decision-making models* when designing and implementing a data-driven culture. Participants largely focused on the relationship of decision-making to data-driven technologies, largely agreeing that in data-driven organizations, decisions are made with additional knowledge provided through data. Participant 8 acknowledged the frequent bias inherent in organizational decision-making, stating, “Many times, specifically in my position, decisions get made based off of emotion.” Participant 10 explained that data-driven decision-making should be visible in the organization, especially when using the practice to avoid emotionally-charged decisions: “I think it’s something you see. I think it’s something your employees start to exhibit. They start to use data instead of emotion around decision-making. Using data around decision-making leads to better results.” Some participants acknowledged the usefulness of decisions made using data and how more informed choice selection results in better organizational performance. Participant 9 explained that when decisions are made with the benefit of additional knowledge, choices are made more quickly and the organization profits from better decision-making: “We could have different decisions being made, maybe bigger decisions being made, more quickly or see our costs go down.” Participant 11 described data-driven decision models as being more scientific in the way an organization in managed: “Did the business make their decisions based on the data? So, they’re going to be looking at, you know… it’s kind of a scientific approach to managing the business.” Understanding the ways in which decisions are made in the specific organization can help inform what needs to change to introduce a data-driven culture. If decisions are being made through emotion, participants explained that decision-makers in the company should, at a minimum, seek to find additional information through data-driven technologies to supplement their decision-making process.

Several participants addressed the *purpose of data*, suggesting that organizations should ensure understanding of the ways data can be used before embarking on a data-driven culture transformation. Researchers agree that organizations should possess this understanding. Garcia-Perez (2018) and Halaweh and El Massry (2015) explained that such a culture is intended to transform decision-making strategies into scientific, rather than emotional, affairs. Shrestha et al. (2019) focused on the role of technology, explaining that, where possible, data-driven systems are intended to apply reason-based decision-making to operational choices. Gauzelina and

Bentza (2017) and Ward et al. (2019) argued that human decision-making is fundamentally irrational and that technology, while still imperfect, allows a degree of control over decision-making that improves the quality of choices made. Five participants of 18, or 28%, addressed the need for understanding why data-driven decision-making is necessary in an organization. Participant 6, for example, explained that data are used to help drive daily decisions and to help the business plan for future strategy: "We try to use data and accurate reporting and real-time reporting along with… to help drive our decisions and how we operate both on a daily basis and on a future planning basis." Participant 15 stated that data can be used as a decision tool that can help protect against invalid emotional choices:

> It's really easy to think that you have a feel for the way things are going, but sometimes your gut feelings are incorrect, and so it's always good to back that up with data so that you can make intelligent decisions on a variety of different things, whether it be on performance, business production, cost savings… you always want to have hard evidence before you make decisions on those things.

Knowing why decisions are made with the support of data, participants stated, is necessary for building the desired data-driven culture. Without such understanding, the organization risks allowing decisions to continue being made using solely emotional methodologies that deliberately avoid the input of data.

As a corollary of the purpose of data, participants frequently discussed the use of *data as a metric*. Data allows business leaders and individuals to understand performance and how organizational functions relate to one another and inform each other. Researchers support the idea of using metrics to understand and make change within the organization. Mikalef et al. (2018) explained that operational data and decision-making shape and influence the aggregate results at the highest levels of the organization. Mendes et al. (2018) and Weiner et al. (2015) showed that decision-making must occur in a hierarchy of operational, tactical, and strategic actions. When goals at each level and decisions are in sync, businesses are able to form a cohesive group that relies on data to drive choices (Mendes et al., 2018; Weiner et al., 2015). Seven of the 18 participants, or 39%, explained the importance of using data to describe the performance of the company. Participant 17 compared organizational performance to a game with a scoreboard, explaining that people want to know what results were achieved: “Who doesn’t want to see the score? I’ve never met very many people that played a game that didn’t want to see what the score was. They want to see where they finished. So, I think that’s very important.” In a general sense, participants described the desire to understand performance through the use of data, as well as the ways data can be used to improve performance. Participant 15 explained that individual metrics should be provided and applied to the overall company goals so that employees can understand how their performance impacts the rest of the organization:

> You have to have benchmarking in place, and goals, and regular reporting, so that every employee in the organization knows how they are performing. A scoreboard, for lack of a better term, towards a bigger goal. The overarching company goal.

Participant 16 described the ways data can be used to measure performance but in such a way that drives improvement, specifically through the use of coaching and fostering a sense of healthy competition among employees: “It’s coaching through data. It’s using data to measure someone’s performance, and to put it out there and create healthy competition, and all the good things that come from data.” Using data to model organizational performance is a necessary way to provide leaders and employees the information they need to alter their decision-making processes. Data, as metrics, is an enabling technology that allows individuals to adopt data-driven decision-making.

Despite overwhelming support for the use of data in decision-making, participants were hesitant to claim that all decisions should be made completely through data. Some participants instead offered the concept of *data as a decision-making supplement*. This concept was backed by several researchers as well who stop short of claiming that technology can act as a complete substitution for human thinking and intuition. Researchers frequently affirm that data can supplement human decision-making to create wiser, faster, and more informed choices (Gauzelina & Bentza, 2017; Pranjic, 2018; Reymen et al., 2017; Ward et al., 2019). Similarly, Benmoussa et al. (2018) showed that data can be used as a decision support tool that provides evidence backing a certain position, although data itself cannot always make a final determination. Two participants of the 18 in the study, or 11%, identified the role of data as a decision support tool. These participants explained that data is one part of the decision-making tool belt that must be used in conjunction with other tools before a decision can be made. Participant 13 explained that decision-makers must be careful to include other inputs when making choices, especially due to the sometimes-misleading pictures that data provides:

> You know, when I think about a data-driven culture… it's something I think we get caught up in numbers, and sometimes they're not just… numbers are not always accurate and you can't always make a hasty decision just by data alone.

Participant 10 acknowledged that creating a completely autonomous business would be an ideal situation, but explained that technology, especially in the transportation and logistics industries, does not yet support this sort of decision-making model:

> So, I've always kind of referred to it as a data and IT-augmented business, not necessarily an automated business. That's been difficult for me to understand, because I'm always, I'm inherently wanting things to be efficient, and if I want things to be efficient, I don't want anybody working for me. But we're just not there yet as an industry.

Using data to supplement existing decision-making processes, according to participants, is the most effective way to improve decision-making. Due to the limitations of technology, humans are still needed to make more complex choices, though data can still provide guidance in these situations as well.

Continuing the premise that data should be used as a decision-making supplement with moderated automation, participants discussed the need for organizations to observe the *people element of business*. Participants explained that businesses cannot become completely autonomous due to the need for human intuition in decision-making. Cao (2017) described the limitations of technology, explaining that data-driven systems may never be as complex and intuitive as the human brain. Researchers make sure to acknowledge that data-driven technologies should be understood to largely be tools to support decision-making and that current technology is no perfect replacement for human intuition and experience (Bogdan & Lungescu, 2018; Cao, 2017; Galbraith, 2014; Grover et al., 2018). Decision-makers are frequently presented with choices and minimal information with which to make a selection (Amariei & Hamat, 2018; Fomin et al., 2016; Marewski et al., 2018; Reymen et al., 2017). In these situations, decision-makers must rely on intuition to make a choice (Amariei & Hamat, 2018). This intuition allows humans to make creative leaps and bridge the gap between known information and decision inputs (Amariei & Hamat, 2018; Reymen et al., 2017).

A significant number of participants, 12 of 18 (or 67%), mentioned that humans still have a role in business even after they become data-driven. Participants focused both on the positive aspects humans bring to decision-making and the negative aspects of data that can be avoided by maintaining human involvement in most non-autonomous decision-making. Participant 6 explained that humans bring intuition into decision-making and that humans must frequently make the final choice in a matter, even when decisions are supplemented by data:

> I think sometimes if you become too data-driven, then I think that we lose what individuals bring to the table for decision-making, for things like that, because I think it's all part of it. […] In the end I think you've got to have those people and that's the reason you have those, you hire those people and you bring them in to make those decisions.

Participant 16 argued that a lack of human involvement places undue risk on the organization due to a lack of input and feedback, as well as complacency:

> I would think that the risks would be that you may be reluctant to take action, because you're waiting for data to be produced. That would be horrible. Where you're no longer trusting your gut. So, I think that that would be a drawback from being overly data-driven.

Some participants called out the possibility that employees can become dehumanized if viewed as only a metric. Participant 12 cautioned that the organization must continue to see individuals as humans and treat them with respect while balancing the benefits of becoming data-driven:

> Not being somewhat emotional or tied to feelings, just all data… I guess it might make you a little cold-blooded, like Mr. Spock. He was always one that was just… just the facts. Point blank. I think you have to have some balance there, with the emotional side of things, the human side of things.

Participant 17 concurred, explaining that dehumanizing employees has a negative effect on morale and culture in the organization: “You get tunnel vision. Maybe if you’re not careful you lose touch with the people that are working for you, that you need. And then it hurts your culture.” Organizations must avoid alienating their people when creating a data-driven culture. Change coalitions should ensure that individuals are still part of the decision-making process where necessary, and work to guarantee that individual employees are still treated with respect.

Understanding the decision-making processes that individuals within the organization utilize is necessary to appropriately transform a culture into one that relies on data to make decisions. This requires knowledge of key decision-making processes and understanding the purpose and potential use cases of data. Participants also discussed the role of data in a supplemental decision-making role, as well as the necessity of continuing to utilize humans in decision-making procedures. Additional supporting statements for each of the identified themes regarding decision-making processes are given in Table 8.

Table 8

Identified Themes and Supporting Statements – Decision-Making Processes

Identified Theme	Supporting Statements
Decision-making models	“I think once you’re able to make decisions off the data, off the data analysis, and the business decisions you’re making are yielding results, I think that’s when you start to be a success.”
	“I would say when decisions aren’t made out of opinion but they’re made out of numbers.”
	“Well, when a lot of your business decisions are based on your data.”
Purpose of data	“How do we really use that data to get better?”
	“The more data you collect over time, helps you to understand maybe trends in the business and the marketplace, helps you to avoid some issues because you have history, you’ve seen this before. It’s not just

	anecdotal information. You can actually apply some logic to it, to help you guide that business."
Data as metric	"How do you know where you're going? How do you know what to change?"
	"Seeing how people explain the successes or the failures of their business, whether they explain it to just making excuses, or actually understanding the numbers and then reporting back on why these numbers impact other numbers and what they can do better to improve those numbers."
People element of business	"You take the person out of that sequence it can be a little scary because you don't really trust that data."
	"If you're just data-driven, then you probably don't care about the people aspect of things. If you're the most efficient then you're not really accounting for peoples' flaws."
	"You could lose focus on employee morale. Could cause high turnover because you're so focused on that end result or goal that you're not maintaining relations with the staff."
	"One thing I don't believe in is trying to become completely driven off the data and lose sight of what… the people and interaction of the people and what they bring to the table as well."
	"Obviously, you've got to have a little gut feel on things."
	"To me, the biggest risk is the human element of this industry and not breaking that but actually enhancing it, how to take the data and enhance that piece."
	"That you sometimes lose the human touch of it. Where you don't make… everything is given to you in a report, and you don't think about it as much, or you get too mechanical."

Subtheme: Goal-Setting and Project Prioritization. Participants frequently discussed the need for business intelligence teams to understand the levers by which organizational goals are set and prioritized. This refers first to organizations placing a high priority on data-driven initiatives and second to the prioritization of projects assigned to business intelligence teams. All 18 participants discussed at some length the ways a business should prioritize their work.

Participants focused on the responsibility of goal-setting a prioritization in a business, as well as the project selection methodologies that should be employed. Whereas the first theme identified discussed persuading decision-makers to utilize data-driven technologies at a micro-level scale, this theme is intended to represent how data-driven projects can be socialized to a wider audience. Participants generally stated that goal-setting should be the responsibility of (a) leadership, (b) committees, or (c) through a common effort between management and employees. Furthermore, participants explained that prioritization should be driven by (a) financial impact, (b) company goals, (c) gaps, or (d) available resources.

Researchers largely point to leadership to prioritize what work needs to be complete and where resources need to be directed. Mohagheghi et al. (2019) explained that firm managers should be responsible for identifying and prioritizing work. Pedersen (2016) stated that project portfolio managers should own project prioritization and set goals for the organization. Leyva-Vazquez et al. (2020) and Zenglian et al. (2017) explained that analysts should analyze the return-on-investment for projects and report these to leaders for a final decision. Grubljesic and Jaklic (2015) discussed the need for business intelligence teams to be represented in prioritization discussions and for a strong executive sponsor to support efforts at the highest levels. This sponsor also facilitates the permeation of project goals throughout the entire business (Mesaros et al., 2016). When analyzing participant beliefs on the responsibility for goal setting, Mohagheghi et al. (2019) most closely aligned with a top-down design. Pedersen (2016) resembled the committee-driven approach, while Leyva-Vazquez et al. (2020) and Zenglian et al. (2017) identified most closely with a common responsibility approach.

Participants were somewhat divided in beliefs regarding who is responsible for decision-making regarding project selection and prioritization in an organization. Several participants discussed multiple methodologies and acknowledged that methodologies are not necessarily mutually exclusive. Out of the 18 participants in the study, 11, or 61%, positively discussed *top-down goal setting*. These participants explained that goals should be set by top management, with middle managers setting tactical goals. Participant 8, a member of the organization's leadership team, explained that departmental goals should be based on and aligned with the overall goals of the organization:

> So, in essence, when we set goals in the company, […] you set an overlying goal of the organization. We want to make this much money, we want to be this safe, and we want to do this many miles. And then each department below that sets cascading goals that lead up to that main goal.

Participant 1 explained that executive leadership possesses insight and knowledge that helps them best make a well-rounded decision regarding priorities, explaining that other members of the organization may not have the information necessary to make a sound decision:

> I do think that you need somebody in upper management to help essentially determine what is most important in the organization because that individual is probably going to be exposed to all the decisions made by the executives and the board and know really where we need to drive the business.

Participant 10, another leader in the organization, explained that goal-setting should occur through a team of management near the top of the business, but lamented that often organizations must rely on executive leadership in the face of a maturity gap:

> I want to say the executive leadership, but I feel that we do that because currently there's not enough maturity at the next levels… at the other levels of management down. They just want what they want, and not necessarily what the right thing for the company is.

> Long-term, I think it should happen below the executive level, unless it is a significant investment.

Top-down goal setting was a popular topic of discussion among participants. Organizations should, according to these participants, set organizational goals and allow individual departments to set their own goals that are in alignment with those of the business.

Several participants discussed the possibility of utilizing committees to drive project selection and prioritization. These participants believed that committees should be employed to make decisions about projects as a group. These committees may include a team of executive leaders, project managers, analysts, or others who come together with the purpose of selecting and prioritizing the most important projects in the organization. Seven of 18 participants, or 39%, identified *committee-driven goal setting* as an effective methodology. Participant 16 explained that department heads should identify projects and that this work should be prioritized as a joint effort between leadership and a project selection and prioritization committee:

> Well, I think each department, or head of the department, should manage their use cases. And if you're talking about how we know what to work on first, I would say that it comes from the executive team and the [project prioritization meeting] in the case of our organization, to prioritize what we deliver first.

This prioritization committee, according to participants, should conduct regular meetings where the benefits, drawbacks, and financial impacts of each project should be discussed. The committee may then decide whether to adopt, terminate, or reprioritize individual projects. Participant 14 explained that committees should be responsible for prioritizing projects and should do so based on the total value of the project to the company: "At that point, it would be our enterprise project committee, where they would meet and see which one is more important, and that would provide more value to the company as a whole." Participant 6 identified a host of individuals that should be included on a prioritization committee, explaining that operators, financial departments, and technical groups should be represented in decision-making so that committees can make the best possible decisions:

> I think it's one of those deals where you've got to have a group of people looking at it both from the business side, the financial side, and the technical side, to figure out really, truly, what cost is and what the benefit is going to be for something.

According to participants, some organizations may find value in allowing project selection and prioritization to be completed by a committee. Under this design, a committee is tasked with understanding and prioritizing all major organizational projects. In this way, selection and prioritization receives the input and blessing of leaders from all areas of the organization.

A final set of participants argued that decisions regarding project prioritization should be made in collaboration between leaders, managers, and workers. Under this design, leaders would retain ultimate decision-making power but solicit the input of workers with responsibility over certain areas. Of the 18 participants in the study, 10, or 56%, spoke favorably of *common responsibility for goals*. When asked if prioritization should be a collaborative activity between workers and management, Participant 5 responded affirmatively. Participant 8, a leader in the organization, explained that although executive leadership should be the ultimate decision-maker of project prioritization, front-line workers should be able to provide feedback to leaders to provide management with the perspective of somebody closer to the operations of the business: "Actually, it should be a push and pull on the information because your lower individuals, the people on the front lines, should tell you, 'This decision is not working, and this is the reason why.'"

Participant 11 provided a model for decision-making regarding the prioritization of technical projects, explaining that a collaborative effort would result in the best decisions: "I think I would say management, executive management, and IT need to come together… IT more in a kind of supportive role, saying, 'We can provide this information' or, 'No, we don't have that level of data.'"

Participant 3 agreed with this stance, explaining that front-line workers can provide valuable insight regarding what can and cannot be completed, or what efforts would be required to accomplish the goals of leadership:

> I think that the analyst that's over the development should be involved in that prioritization. They're going to kind of know what it takes to gather, or have a general idea of what it takes to get from A to B.

Under a collaborative-style design, participants explain that leaders would work with individual operators to set the priority of projects. According to participants, this gives operators a voice in decision-making regarding project selection and helps leaders better understand project considerations and the impact their decisions have on the organization.

Participants were also split over the methodologies organizations should use to prioritize data-driven projects. Over half of participants mentioned selecting projects with the highest financial impact or projects that would fill known gaps in the organization. Other significant methodologies uncovered included following executive priorities or by completing projects as resources become available. Researchers provide a host of different ways organizations can prioritize projects, with most suggesting a combination of methodologies. Mohagheghi et al. (2019) offered three distinct factors that should be considered, including financial impact, social preferences, and environmental priorities. Pedersen (2016) explained that projects should first be prioritized based on organizational goals, then on political pressures and intuition. Leyva-Vazquez et al. (2020) argued that organizations can narrow the list of potential projects by identifying only those that follow the stated goals, then use financial tools such as returns-on-investment and net-present-value analyses to determine financial impact. Zenglian et al. (2017) encouraged organizations to use these financial tools as well. According to Grubljesic and Jaklic (2015), projects that are specifically data-driven should be prioritized when they are simple and have a high rate of return.

Participants selected a diverse set of methodologies for prioritizing projects. Methodologies discussed are not necessarily mutually exclusive, and many participants discussed favorably more than one methodology. Many participants discussed the need to prioritize work based on the expected impact of projects. This methodology involves understanding the anticipated financial impact of projects and sorting based on those that have the highest rate of return. A high number of participants, 13 of 18, or 72%, discussed the concept of *impact-driven data analysis*. Participants discussed the need to understand projects' impact on profit so that they can be prioritized. Participant 10 explained that in regard to data-driven opportunities, organizations should organize priorities by potential impact to profit:

> Easy… profit-based. The quickest way to gain trust in a for-profit business is drive profit while either increasing revenue or decreasing cost. I think, specific to that question in gaining trust that will immediately garner a level of trust that you won't gain from any other method.

Participant 9 corroborated this claim, explaining that decisions regarding priority should be based on potential revenue: "Honestly, I'd probably go with what makes the money. And that can be a big driving factor. What's going to give us the most revenue?" After establishing that financial-based prioritization is the proper way to sort potential work, Participant 8 explained the process by which this ranking should occur:

> If I was a data scientist, I would sit with the financial gurus in the company and find out where our biggest pain points are, and those are the things I would concentrate on first to build the rapport and trust and show that this data, if we were to make these decisions, it would affect us and benefit us financially.

Demonstrating the projected financial impact is key to work being highly prioritized, according to this group of participants. Participant 15 explained a similar process, adding that prioritization should also consider what resource constraints may exist:

> Generally my recommendation would always go to the highest leverage activities first, so the way that I would do it is just kind of list out everything, then do a weighted scale based on the impact it would have on the organization, whether it be on the cost side or on the revenue side, and then prioritize based on that and what your internal resources will allow.

This large group of participants agreed that impact-based project selection and prioritization would be the most appropriate way to sort work for business intelligence teams. Using potential revenue gains and cost savings to model impact to profitability, those tasked with prioritizing projects should work to understand which projects would have the highest impact and recommend these for undertaking.

A second group of participants identified *goal-driven data analysis* as an appropriate methodology for organizing project work. These participants explained that executive priorities should drive what projects are given high urgency. Although executive priorities may themselves be based on financial impact, these priorities may also include political, social, or environmental factors. Six participants of 18 in the study, or 33%, explained that executive goals should be considered when deciding which projects to undertake. Participant 2 stated that managers should decide what organizational goals should be so that teams know how to prioritize their work, explaining, “Your managers are going to have to implement goals or determine what the goals are.” Participant 5 expanded on this thought, arguing that projects that are important to management should be prioritized favorably: “If it is something that is important to management, you need more… helping them on some of the metrics.” Although participants were generally supportive of using executive goals to prioritize data-driven projects, four of the six participants who supported goal-driven prioritization, or 67%, also mentioned other forms of project selection and sorting. Participant 9, for example, supported prioritization informed by goals, but only in a supplemental role: “Those are some ways to prioritize as well, and I mean, we go with goals, but I don’t necessarily think what we work on for these are just about goal-driven.” Participants did not eliminate the possibility of using executive goals to drive project prioritization, though their response was less enthusiastic than that of financial-driven rankings. At a minimum, those responsible for project prioritization can use executive goals to tangentially inform their decisions.

A large, third subset of participants explained that *gap-driven data analysis* can influence project selection and prioritization. In this group, participants believed that organizations should identify the gaps in their organization and find inefficiencies, then match projects to these gaps and select projects that best fill the largest of these. Using gaps to prioritize projects was discussed by 10 of 18 participants, or 56% of respondents. Many participants discussed the need for analysts to meet with business owners to identify projects and prioritize based on gaps. Participant 11 explained the process of meeting with owners, explaining that the goal should be identifying what items are needed to better manage their organization: “I would say that working with a business owner, you need to define what their needs are, so what is it that they think that they need to effectively manage?” Once gaps are identified and potential projects have been discussed, one participant discussed the need for a centralized repository for storing work that needs to be prioritized. Participant 14 stated that analysts should meet with various departments and keep requests in one easily-accessible location:

> I really think if we have analysts that could get with the different departments and identify their struggles, and bring all of that to the table, and we can provide a center, a central location for them to go to see.

Meeting with business owners is a useful way to understand what gaps appear in the organization. Participant 18 affirmed that analysts should work with business owners when investigating processes and looking for gaps: “They’re looking for issues and then going down the path of trying to figure out solutions talking with the operations folks, investigating the process, identifying the problem. I think that should be their duty.” When analysts meet with business owners, they must find ways to identify gaps. This typically involves a form of process understanding. Participant 9 confirmed the need for identifying gaps in project selection and prioritization:

> Basically, going through their processes and determining what their processes are, and tying in what we gather for our data for each of those business processes, and seeing, ‘Well, do we need some more visibility to this thing over here? Are we measuring this thing over here, but we just don’t know all the components in the data that would be involved in it?’

Participant 16 described a top-down approach to gap identification, identifying a rigorous, technology-minded process by which organizations can prioritize their project selections:

> For me, I'm a top-down thinker, so I would say you need to start at the top and understand what drives your business today, and what are your gaps that you don't have that you wish you had, and for me, I would say you've got to establish the dashboard, the vision picture, and that will drive each level down in terms of reporting, and you'll be able to see real quickly, we don't even store this piece of data right now, but you're telling me it's key to your… the insights you need to be able to identify how frequently we should buy new tires, or whatever.

Using gaps to identify which projects should be selected and prioritized was favored by a number of participants. These participants each suggested working with business owners to identify what is missing and what can be bridged to make the organization more effective. In doing so, those responsible for prioritization can best understand what projects can provide the most useful information to business owners.

A final group of participants explained that a *resource-based strategy* can help inform project selection and prioritization as well. This strategy involves identifying the resources it will take to finish a project and selecting projects that utilize currently-available assets and, preferably, a small number of resources. Five of the 18 participants, or 28%, mentioned a resource-based approach to project prioritization. Participant 6 explained that projects should be selected, prioritized, and designed based on what resources are available: "How much time do you have, and how many resources do you have? What's the easy button? What's the easiest way to get it to you?" Participant 2 stated that projects should be prioritized according to what data are available and noted that external resources could be called upon to increase project capacity if resources are too constrained: “I think it depends on what data they have readily available, and what type of resources they have internally to differentiate what they need externally, versus internally.” Participant 9 warned that projects selected using a resource-based approach should be fairly small and should be easy and quick to implement: “One of the things is not to bite off too big of a goal. Possibly just picking the top three things we want to work on, and get them done.” Participants who suggested a resource-based strategy again did not specify that it could not be used in conjunction with other strategies. Most participants indicated that resource-based prioritization may act as a supplement but not a replacement for more effective forms of project selection, such as impact-driven or gap-driven project ranking.

Participants failed to reach a definitive consensus regarding project selection and prioritization methodologies, though provided a list of several strategies that, taken as a whole, can inform decision-makers’ selection criteria. Participants identified impact-driven and gap-driven methodologies as two highly useful ways to organize project work for a business intelligence team. Furthermore, participants explained that goal-driven and resource-based methodologies provide an additional layer of tools that can help further supplement prioritization decisions. Table 9 explains beliefs of each participant and provides each participant’s level in the organization, participant understanding of the responsibility of project selection, and beliefs surrounding project selection and prioritization methodologies.

Table 9

Participant Beliefs on Project Selection Responsibility and Methodology

Participant	Level	Responsibility	Selection methodology
1	Manager	Top-down	Goal
2	Manager	Top-down or committee	Impact, goal, gap, or resource

3	Employee	Top-down or common	Impact or resource
4	Manager	Common	Impact
5	Employee	Common	Impact, goal, or gap
6	Manager	Committee or common	Impact, gap, or resource
7	Employee	Top-down	Impact or goal
8	Leadership	Top-down, committee, or common	Impact
9	Employee	Top-down or common	Impact, goal, gap, or resource
10	Leadership	Top-down or committee	Impact or gap
11	Employee	Committee or common	Impact or gap
12	Employee	Top-down or common	Gap or resource
13	Manager	Top-down	Impact
14	Employee	Committee	Gap
15	Manager	Top-down or common	Impact
16	Leadership	Top-down or committee	Gap
17	Manager	None specified	Goal
18	Leadership	Common	Impact

Participants occasionally discussed the need for *routine reviews of goals*. These reviews allow organizations to periodically check progress on each project and reprioritize or select new goals if necessary. Four of 18 participants, or 22%, identified these reviews as a necessary part of the data-driven project management process. Participant 16, referring to project prioritization, explained, “That’ll probably change, needs to be re-reviewed, but that’s where I would start.” Participant 8 went into further detail, explaining that the importance of particular projects may fluctuate over time:

> And so what's important right now will not be important a year from now, six months from now, maybe even a month from now based on those changes that you make and things will change based on how you make changes to what you're doing, and so that data is going to have to flow on a regular basis.

These routine reviews, according to participants, should take the form of meetings where projects are tracked with hard data and roadblocks can be identified and eliminated. Participant 17 explained that reviews should seek to understand progress and move projects forward:

> You need to meet regularly, track where you're at, and if you meet regularly and you're tracking, you'll be able to say, 'This guy has been at 30% completion for three months. What's our roadblock and what do we need to do?' Not this guy, but this particular project within the project or within the program. Regular meetings, tracking of progress.

Reviewing progress and reprioritizing when necessary is an important aspect of a data-driven environment. This may especially be true when discussing projects of a larger scale due to shifting organizational needs. Data-driven teams should seek to identify and prioritize work based on the needs of the organization, indicating that projects should be reviewed periodically for status reports and relevancy.

Business intelligence teams should actively be involved in the goal-setting and prioritization of projects within an organization. Organizations should decide and teams should understand who is responsible for enterprise project selection and prioritization within the business. Participants offered (a) leadership, (b) committees, and (c) collaborative ventures as possible areas of responsibility, with most agreeing that executive leaders are the ultimate decision-makers in matters of prioritization. Those surveyed for the study also determined that decisions of project selection and prioritization should be made with consideration given to (a) financial impact, (b) non-financial organizational goals, (c) gaps in the business, and (d) available resources. Participants also explained that goals and priorities should be reviewed on a regular basis and updated using the latest information available. Table 10 provides additional supporting statements for the identified themes relating to project selection and prioritization.

Table 10

Identified Themes and Supporting Statements – Goal-Setting and Prioritization

Identified Theme	Supporting Statements
Top-down goal-setting	"I also think management is necessary for goal-setting."
	"Your direct boss would…"
	"I think the only person that can really be responsible for it is the business leaders."
	"I think a leader has to, like I said, a leader has to set the bar. They kind of set expectations. They have to be the ones that say, 'These are the results we expect to get.'"
	"I think that comes from your executive team."
Committee-driven goal-setting	"I think we do somewhat of a good job determining priorities because we have a whole group that does it."
	"I love the [project prioritization] process that we have. I feel like that could really be the project management process that we have."
	"I'm kind of of the mindset that it's almost maybe the committee approach."
Common responsibility for goals	"Personally I would… a lot of times, the person prioritizes, or their manager will."
	"The only way to really do that is working with the teams that are going to be using the data."
	"I would say some of the smarter groups would be wise to ask what the priority of the analyst would be, then bound that… have a conversation and a dialogue about, what do the analysts think?"

	"I think it's between the operators and their analysts. And then finally, I would say [Financial Planning and Analysis] is probably constantly looking for solutions, or should be if they're not."
Impact-driven data analysis	"I think that priorities are generally the highest cost savings or the… what is going to increase profitability the most."
	"That's one of those things where you find those five projects and find which one takes the longest or has the biggest… most financial impact, and you'd prioritize it that way."
	"I would say one of the first ones would be using data to improve performance. Whether that be revenue or profitability."
	"I think… most businesses know what number they want to move, and that's revenue."
	"It's like anything else, you've got to be able to do a good ROI on everything."
	"And then also helping them understand that maybe sometimes what they think is a priority doesn't really have that big of an impact financially, and then helping them kind of push them toward that thing that's really going to have a larger impact, that's going to close the gap between us and other companies."
	"You're going to have to look at what affects the strength of the company, which is usually your revenue, but I think that with each department, having the ability to look at their data, and have their data available to them, individually, individuals would be able to identify within their own departments what effect that's having."
	"It all ends up bottom line, if there's a financial impact to the company one way or the other, but it's kind of the focus of that particularly department of the business."
	"I think they have to identify what is most important to the organization? What drives these biggest results and successes and identify from there."
	"Anything that's worth a million dollars that's proven with data, is probably a big problem that's solvable with data."
Goal-driven data analysis	"I think they have to know what the goal is, and then what impacts that data."
	"I think the only way you really know what to prioritize is by interacting with the people that actually use the data. […] The only

	way you know what's going to be most important for them to understand is… the problem areas of their business and the problem areas they're targeting to improve."
Gap-driven data analysis	"I think having metrics that you can pull and look at regularly, and looking at trends or issues in reporting, or inconsistencies, that's where you find what your priorities are."
	"Gap analysis would be important to any area of the business, but somebody in Safety is not going to be necessarily looking at revenue per load, they're going to be concerned with violations, accident rate, things of that nature."
	"One of the ways you can do it is, I think you just have to go to the end users, the people that are actually using it, because ultimately those are the ones it is going to affect the most… things such as surveys and job shadowing would add into providing some insight into how that software or system was going to best be utilized to drive the results."

Subtheme: Team Management. Several participants discussed the ways data-driven teams should be managed for maximum effectiveness. Executive leadership should take some considerations when managing teams for these teams to be most productive. Participants explained that in the absence of issues that need additional attention, teams should be treated with respect and trust. This indicates that leaders should trust teams to self-govern, make decisions about methodologies within reason internally, and remove barriers to progress. Participants specifically discussed the need for leaders to invest in technology, empower analysts, and participate in a somewhat hands-off supervisory role. Some 10 of 18 participants, or 56%, mentioned one or more of these activities as an important component of team management.

Various participants discussed the importance of *investing in technology* and *investing in analysts*. Leaders should, according to participants in the study, provide business intelligence teams with the tools and resources needed to effectively complete their work. Although this funding must be provided responsibility, leaders should be willing to consider requests for additional tools or resources. Researchers generally agree, stating that investment in business intelligence technologies correlates to data maturity (Chen & Nath, 2018). Salmasi et al. (2016) explained that investments in technology allow organizations to collect, store, and manage data responsibly and take concrete steps toward data maturity. According to researchers, business analysts and data scientists should communicate what tools and investments should be made to improve business intelligence processes and ultimately data maturity (Boncea et al., 2017; Salmasi et al., 2016). Other researchers take a wider stance, explaining that investments into becoming data-driven must also include allocating resources for altering processes and culture (Al Rashdi & Nair, 2017; Lawler & Joseph, 2017).

Participants in the study were generally supportive of the need to invest in technology. Individuals surveyed largely built a consensus that technology should be respected as a way to improve the operations of the business. Furthermore, participants stated that investments may be in human resources or in technical needs. In total, eight of 18 participants, or 44%, agreed that technology should be a focus for investment in an organization. Participant 6 explained that if an organization wants to be a leader in technology, financial resources should be dedicated to data-driven solutions:

> You've got to invest in it, and keep on going down that road where, 'Hey, we want to be in the leading edge of technology and the leading edge of solutions. We want to be the best at what we do and how we do it.' Then you've got to stop and reevaluate your current situation and see what the possibilities are.

When organizations set out to determine levels of funding for IT projects, participants explained that leaders should treat IT with respect and understand its value. Participant 8, a leader in the organization, argued that IT can provide great insights into improving the operations of the business and have value beyond traditional roles:

> So, I think that's going to be the genesis of this change, is getting and seeing the value of what IT can give to a company. They're no longer the guy you put in an office and feed pizza under the door to until they get their job done… but they're actually interactive individuals within the operations of the business.

Some participants discussed the need to invest in tools in addition to headcount. Participants explained that organizations should identify and acquire, when possible, modern technologies that facilitate the discovery of valuable insights. Participant 4 described the need for organizations to invest beyond antiquated technology and provide tools that analysts need to be most successful:

> But the first part starts with having the right tools to be successful. If you're a large organization and you're still trying to manage pen and paper or trying to manage on a spreadsheet, that's probably not very efficient, but as leaders the biggest thing they can do is make sure that analysts have the right tools that allow them to analyze data in an efficient way.

Participant 9 gave more concrete, specific examples of technical investments that must be made, calling out technologies that enable necessary use cases in the arena of business intelligence: "Tools would be any kind of infrastructure, software, places to store their data. Those are all IT infrastructure… and those are all kind of obvious but not necessarily because we want to skim on those things." Participants agreed that if an organization chooses to become data-driven, its leaders should be willing to invest in business intelligence teams, both in headcount and in technical equipment, tools, and resources. This investment facilitates growth in data maturity; a lack of investment is a prohibitive measure that disables business intelligence teams from being able to provide accurate and actionable insights to the organization.

In addition, participants explained that leaders should trust business intelligence teams enough to *empower analysts*. This indicates that business leaders should permit analysts to propose process changes and other modifications to the organization that can help provide an increase to profitability or productivity. Furthermore, business intelligence teams should be empowered to work with members in every area and at all levels of the organization to discover new information, data sources, or processes that may be beneficial in creating insights. Researchers agreed with this, largely confirming the criticality of empowering analysts and removing barriers to success. According to Chen and Nath (2018), the extent to which analysts are empowered to self-govern and conduct internal research is correlated to maturity and is facilitated by leadership perception of IT groups. A supportive culture, according to Cech et al. (2018) and Garcia-Perez (2018), allows business intelligence teams to access additional data and resources; a highly controlled culture without analyst freedom can suppress the ability of teams to provide useful insights. Furthermore, according to Lawler and Joseph (2017) and Skyrius et al. (2016), leadership trust in data-driven teams allows for more reasonable timelines that permit a higher degree of experimentation and documentation. Other researchers argue that empowering analysts can help improve training and development of business intelligence professionals (Boncea et al., 2017).

Some participants called out the need for organizations to empower analysts as well. These participants explained that organizations should respect and trust analysts to provide insightful information. Three participants of 18, or 17%, called out this need. Participant 1, when asked to explain what leaders could do to improve the results of data-driven initiatives, stated, “I think probably empowering them to be able to implement changes." Participant 2, describing the host organization, explained that the company was able to adequately provide resources necessary for conducting robust and accurate data analyses: "I think they were great about getting us the resources that we need to ask and answer questions." Empowering analysts also comprises the need for leaders to make themselves available for follow-up conversations. Participants explained that during the verification and maintenance phase of any data-driven project, analysts should be empowered to discuss outputs with end users to best understand the results of the project. Participant 7 described the need for leaders to communicate effectively with business intelligence teams:

> If [business leaders] never communicate that they need something, that they need to see data, that's going to ultimately be on them, because they can complain about it all they want, but if they never get it into the hands of the right people, then nothing is ever going to be done about it.

Placing trust in business intelligence teams and empowering analysts to work with others across the organization is a useful way for leaders to manage. According to participants, empowering analysts by trusting them to gather information and make recommendations is necessary in data-driven team management.

A necessary corollary of allowing the empowerment of analysts is a certain degree of *hands-off supervision*. To a reasonable extent and as much as possible, leaders should allow data-driven business intelligence teams to self-govern and identify new avenues of research. Although only mentioned by a single participant, this concept's connection to the respect of analysts is clear. Participant 3 discussed the need for managers to trust analysts and avoid micromanagement of business intelligence teams: "I think the management needs to be open to allowing a different set of tools or a different approach, allow that person to think outside the box." In becoming data-driven, analysts must be able to rely on their technical training and make their own decisions about analysis methodologies. Leaders should balance their management of data-driven teams with a hands-off approach to allow for the maximum effectiveness of teams.

Team supervision for business intelligence teams should be rooted in trust and respect. When leaders trust analysts and data scientists to complete tasks and provide actionable insights, teams thrive. However, participants noted that environments marked by a lack of trust are often prohibitive and create barriers to progress. Team management should, according to participants, consist of an appropriate investment in resources and tools, the empowerment of analysts, and a participatory but largely hands-off form of supervision. These activities allow for more efficient work within the cross-functional business intelligence team. Table 11 contains additional supporting statements for the identified themes relating to team management.

Table 11

Identified Themes and Supporting Statements – Team Management

Identified Theme	Supporting Statements
Invest in technology	"… investing in our IT as well…"
	"And so, I see going forward that companies that embrace IT are going to be so much further ahead when it comes to data."
	"Internally I would say that you've got to have the right executive and management team that's willing to pursue those products that are going to enhance your capabilities."
Empower analysts	"Empower them to be able to display that information to the leaders."
	"If [a business leader] asks me to do something for him, and I do it for him, and I get it over to him in a timely manner, but I don't hear anything back on what he thought about it […] then that's, I don't know if that's a tool that he's taking away the ability to get something done quickly, that he asked for, that's going to help him

manage the business, and he's extending the lead time on that. So, him just making the time I guess would be the tool."

Subtheme: Project Management. According to participants, adhering to proper project management practices and IT best practices allows business intelligence teams to maximize the success of projects while fostering trust within the organization. Maintaining speed to market and momentum allows teams to gain the trust and buy-in of top leaders. This should be done without sacrificing quality and best practices. Without explicitly discussing agile development methodologies and minimum viable products, participants explained similar concepts that should be adopted so that teams can most effectively design work and deliverables. In total, nine of 18 participants, or 50%, discussed the need for effective project management in the operations of a data-driven cross-functional team.

Participants first called out the role of *speed to market* in project work. Specifically, participants lamented the frequent lag time incurred when developing new analyses and data-driven systems. These individuals explained that delays in deliverables erode trust in data-driven projects. Agile methodologies, complete with incremental deliverables, can help prevent the perception of slow development, as well as reduce technical debt and improve adoption. By providing a minimum viable product as early as possible, data-driven teams can deploy some functionality to business decision-makers without completely finishing a project. This encourages early buy-in from business users and allows decision-makers to provide feedback that may drive the future of development on the system in question. Researchers are generally supportive of this notion, focusing primarily on the time between a request for information and its eventual delivery. Foster et al. (2015) explained that fast victories help provide credibility to projects and encourage business leaders to continue investing in data-driven teams and projects.

Grubljesic and Jaklic (2015) similarly claimed that simple projects with a high return-on-investment inspire confidence in leaders and potential adopters of data-driven decision-making tools. Cech et al. (2018) encouraged business intelligence teams to complete such projects during the early stages of data maturity so that executives and business users are persuaded to become early adopters.

Participants were highly supportive of the need for projects to be quick to market. Eight participants of 18, or 44%, called out the need for quick returns, with no participants explicitly dissenting. Several participants explained that generating fast results garners support for data-driven initiatives. Participant 11 suggested finding simple projects that teams can undertake, with the purpose of demonstrating capabilities:

> You would want something you could develop relatively quickly, maybe not as complex, easy to validate so you can show the benefit of having that information or having that tool available, so you can show them how quickly we can produce a result that's accurate and consistent.

Similarly, Participant 16 warned that in the absence of results, projects grow stale and change coalitions are unable to transform culture as specified in their strategy:

> And without those quick wins you don't have anything, that guiding coalition won't be able to make good on those promises that we've been talking about. You can have all the strategic direction and clarity and alignment you want, if you're not able to deliver quick wins then you're not going to garner support, and that's key to me.

Some participants explained that without results, leaders begin to question the viability of data-driven projects. These initiatives then become strong candidates for cancellation. Participant 6 explained that trust is eroded when results are not realized and deliverables are not provided:

> The longer you go on something without anything coming out of it, and the longer it goes without leaders seeing anything come out of it, then they tend to lose faith in that it's actually going to get there, or they're going to get anything out of it.

Project teams must set criteria for completing projects and publishing findings before work begins. In doing so, the project completion guidelines are agreed upon prior to the launch of a new initiative. This protects against perpetual projects aiming for perfection that instead become stale, lose momentum, and hemorrhage trust. Participant 8 placed responsibility on data analysts for identifying these situations and preventing them from occurring:

> And so, I think, initially, you would have to go with a financial type model to show and prove out what you're doing, but after that you have to have the courage to say, 'We need to move forward with other aspects of the business.'

Participant 16 similarly discussed the need for moving on to value-adding projects at the point where previous endeavors reach a point of diminishing returns:

> Paralysis through analysis. Sometimes you've just got to… the data is good enough. It's directionally correct. So, if you get yourself to a point where you don't make a move until somebody produces the data and you've got time to play around with it and "what is it" and all of that, sometimes you don't have to do that. It's good enough.

Although no participants explicitly discussed minimum viable product or agile methodologies, those interviewed explained similar concepts of providing incremental improvements to decision-makers. These incremental updates allow decision-makers to begin usage of new tools and allow business intelligence teams to demonstrate improvement over time. Providing quick deliverables to business decision-makers helps build trust between analysts and organizational employees. The absence of speed to market can be highly damaging to the reputation of the business intelligence team and often can result in a severe lack of trust among organizational decision-makers.

Some participants also discussed the need for building and maintaining *momentum* through project management processes. Participants stated that by delivering results quickly and adopting a cadence of regular updates and deliverables, business intelligence teams can keep decision-makers actively engaged in data-driven initiatives. Calof et al. (2017) and Foster et al. (2015) concurred, explaining that in early stages of transforming to a data-driven culture, analysts and data scientists should take advantage of opportunities by seizing momentum. Additionally, Cech et al. (2018) and Grubljesic and Jaklic (2015) stated that quick, regular returns from business intelligence teams can help maintain momentum associated with their work. Two participants of 18, or 11%, called out the need for building and retaining momentum throughout data-driven initiatives. Participant 10 described the way business intelligence teams can transform decision-makers into actively engaged contributors to a data-driven culture:

> And the way that you feed those ideas is people see the benefit. So, you feed an idea and you see that something got better somewhere, whether it's better result, better revenue, better costs, more PTO time, better working conditions, happier customers, happier drivers… if you see that, if they see that, if they see the benefit then next time there will come two ideas, then five ideas, then 50 ideas.

To identify the way organizations can spot momentum, Participant 18 offered the suggestion that momentum can be measured by the initiative of individuals with the business: "When you have somebody in the lower ranks bring a full analysis to you for a problem you didn't know you have, and a solution, and that's when you know you're getting better." Building momentum in a data-driven endeavor helps gain buy-in and trust from decision-makers but also helps create an engaged workforce that is enthusiastic for new information through the platform. Maintaining this through frequent, regular updates to analyses and systems can help teams achieve a level of buy-in and trust from the groups they support.

Following project management procedures and best practices can, according to participants, help drive adoption of technologies and trust in systems. By focusing on speed to market, business intelligence teams can quickly provide solutions in the form of minimum viable products that have a basic level of functionality but provide an immediate improvement to the business decision-makers. Building and maintaining momentum helps elicit enthusiasm from business users that can be highly difficult to duplicate or imitate. Participants largely agreed that adopting a project management approach to team organization and executing on this design will encourage decision-makers throughout the business to provide buy-in and support for data - driven initiatives. A summary of additional support statements for each of the identified themes regarding project management is given in Table 12.

Table 12

Identified Themes and Supporting Statements – Project Management

Identified Theme	Supporting Statements
Speed to market	"I would say not getting stuff back to people, maybe not… like if [a business leader] has something on his mind, like out-of-route miles, and I wait a long, long time to get back to him, then he's probably not going to ask me for that next time, or he's probably not even going to ask because he doesn't trust that I'll have it to him." "… not taking a long, long time to get them done…" "It's got to be swift to market." "I think it goes back to, 'Here's some of our hurdles. Here's some things we can do to improve it, so they can see progress, or see the improvement.'"

Subtheme: System Usage. An often-overlooked aspect of creating a data-driven culture, according to participants, is understand the way individuals in the organization interact with systems, and the way these interactions affect data maturity. Participants explained that, specifically, business intelligence teams should monitor and understand the way data are collected, how third-party systems interact with organizational information, and how automation can impact data maturity. This understanding provides context for data and allows analysts and data scientists to make corrections to processes when deviations are detected. Monitoring the way operators interact with the system provides businesses with the ability to better understand their data and guarantee its accuracy. Providing an intuitive interface for users to interact with core system data can help improve the accuracy and completeness of data.

First, participants noted the need for understanding and monitoring processes around the *collection of data*. This refers to manual data entry processes as well as sensor readings on assets. Researchers identify the collection of data as a key indicator of data maturity (Cech et al., 2018; Chen & Nath, 2018; Farah, 2017). Bajari et al. (2019) explained that the positive effects of data maturity cannot be realized without improvements in the collection and storage of data. The proper collection of data, including building intuitive, error-free user interfaces and automated processes to read sensor data, is facilitated by information technology departments and is a critical-path item in the development of any data-driven initiative (Berman et al., 2018; Brynjolfsson & McElheran, 2016; Zhang et al., 2018).

Seven of 18 participants, or 39%, discussed the need to monitor the collection of data. Participants stated that the proper gathering of data and monitoring system interactions, as well as intuitive system design, is necessary for enabling data maturity. Participant 9 explained that a data-driven culture requires the collection of data in a way that enables its usefulness: “Because it’s data-driven, we need to figure out how to gather it and store it, put it in ways we can actually make it usable.” Participant 6 elaborated on the importance of collection of data, adding that increased attention on data can help drive proper collection and interaction with systems: “When you start to rely on that data, you’re going to get better about how you both capture the data, process the data, and deliver the data to the business.” The scope of data generators in the company includes the entire business. All members of an organization interact with technology in some way and can be considered system users of at least one piece of technology. Participant 10 explains the widespread creation of data, implying that users across the business must be encouraged to follow standardized processes for interacting with operational systems:

> It starts with the input, so you’ve got every employee in the company, in this day and age, every employee in the company is creating data every day. So, you have every employee. And I don’t care… to some extent, even shop mechanics are potentially creating data. If we have an employee that’s in front of a computer, they’re creating data. Drivers create data. Drivers create macros, they’re creating data.

Participants explained that regulating the way employees interact with systems can help improve the consistency and accuracy of information. Participant 12 explained that common processes should be defined, taught, and embedded in the organization, while noting that this can be a struggle within the host organization: “I think with us, our main thing is we don’t have processes in place in some cases or just basic guidelines for the most basic, most essential functions we do, like building an order.” Governing the collection of data and regulating the ways operators work inside key systems can help maintain consistency of data and enable organizations to become more mature. A lack of consistent processes can result in incorrect data that hinders the ability of organizations to make progress toward data maturity and becoming data-driven.

Many organizations, especially mid-sized businesses with a focus outside of technology, rely on outside vendors to provide *third-party software* that can be used to run day-to-day operations of the organization. In these companies, IT departments are responsible for the deployment and sometimes the support of software but not necessarily its core development. Participants explained that, similar to governing the way users interact with software for collecting data, business intelligence teams should monitor how third-party tools can influence the outcomes of data-driven projects. Researchers concur, occasionally discussing the need for evaluating software purchases and their associated business intelligence capabilities. Pappas et al. (2018) explained that enterprise software packages are often information-rich entities that can be leveraged to gain additional data points for use in analyses. Cech et al. (2018) explained that data maturity is reliant upon integrated systems, indicating that information technology departments should be capable of integrating third-party technologies with existing systems and databases. Boncea et al. (2017) encouraged organizations to evaluate third-party software solutions prior to purchasing, specifically suggesting that the company look for solutions that improve technical maturity. In this way, organizations and business intelligence teams can ensure that these software packages satisfy the needs of a data-driven business.

A small number of participants, three of 18, or 17%, discussed the need for evaluating third-party software solutions and monitoring their implementations. Participants argued that implementations should be personalized and that data can be made available. Participant 10 explained that data are shared through third-party entities between customers, logistics carriers, and the host organization: “Depending on what you do, external parties are important too. You’ve got customers who are sending us data. You have carriers now sending us data, through things like [tracking software]. You’ve got third parties that are sending data.” Specific to third-party vendors, Participant 12 discussed the importance of developing relationships with providers and creating mutually-beneficial partnerships:

> I think externally you have to have a partner that's willing to, whether it be a software company… willing to work closely with you to meet your needs exclusively. That's the problem with the out-of-the-box software that we have. […] You get less personalized approach, I guess, than you would if you had a business partner that was catering solely to your needs or more in tune with your needs.

When these partnerships are developed, organizations are more equipped to customize software to their needs and obtain useful data through software packages. Establishing relationships can help organizations improve the usefulness of their purchased software and can help business intelligence teams gain additional access to the software's data. Furthermore, these relationships can be beneficial when trying to understand the software's internal logic and how data can be used in business intelligence projects.

Participants discussed the *effect of automation* on data-driven cultures, explaining that automation can provide an additional level of accuracy and greatly improve the speed with which data are generated. Participants also warned, however, that automation may sometimes lead to a sense of complacency with regard to specific systems. Researchers champion the use of automation where possible, with some arguing that such improvements are often the effect of data-driven solutions. In this way, automation can be both an input and an output of a data-driven culture, depending on the specific use case. According to Demirova (2017), business often find overlap between technological capabilities and business process to identify and eliminate mundane tasks. Such automations can perform operational actions faster and more accurately than humans (Arghir et al., 2019; Bajari et al., 2019; Berman et al., 2018; Haenlein & Kaplan, 2019; Kaplan & Haenlein, 2019; Muller et al., 2018; Nykanen et al., 2016; Popovic et al., 2018; Zhang et al., 2018). When the outputs of automated processes are manipulations or generations of data, such automations provide an improvement in the ability of business intelligence teams to provide accurate insights to the organization.

Several participants in the study noted the role of automation in the host organization. Six of the 18 participants, or 33%, explained that automation can provide more accurate data and better insights, although some acknowledged previous reservations and potential pitfalls of overreliance. As a result of business intelligence endeavors, some participants explained that automation could be a useful measure for cutting costs or allowing employees to focus their time on more value-added activities. These participants explained that by removing the tedious parts of job duties, individual employees can focus on revenue-generating or cost-cutting measures. Participant 8 described the ability of reducing employee responsibilities through automation while simultaneously improving operational decision-making: “Then the next level would be when you can relieve individuals of responsibilities that can be done by computers and put yourself in a situation where the data actually helps you reduce costs and make better decisions.” Participant 16 explained that creating automation, especially through artificial intelligence, can provide employees with a way to eliminate the mundane parts of their job and allow focus on more useful activities:

> On the other hand, another quick win would be to either find a way to help people make better decisions, or take the robot out of the human. That, I think, if you’re thinking about the AI aspect of it, those would be the ways we could get quick wins. Because that hits the ‘What’s in it for me.’

Participant 4 addressed the question of automation from another angle and explained that automation provides cleaner data that can be used in future data-driven analyses, stating, “I also think that you have to have a certain amount of automation to have clean data.” Participant 17, a member of the Operations team, explained initial reluctance to allow automated procedures, though conceded that they eventually became a critical component of company processes:

> Honestly, I was one of the original opponents of [automation], then I became one of the champions of [automation]. And it has some really great benefits that you don’t have to babysit something and manually babysit it. But you can go too far to the other extreme that you never look at that truck, because basically the [automation] is one of those things… like turning on a system, it’ll just keep going until you lock it out or something.

Understanding the role automation plays in the company’s environment can help data analysts provide better insights to decision-makers. In some cases, these automations may be the output of a data-driven project; in other cases, automations may provide a way for business intelligence teams to enhance their abilities and create more actionable insights.

Working with system users to understand their interactions can be of great benefit to data-driven teams. Learning user processes and the way software interacts with underlying data can help provide business intelligence professionals with the intuition and understanding necessary to provide better insights to decision-makers. According to participants, this involves understanding how systems collect data from employees, how third-party systems interact with the organization’s environment, and the role automation plays. Participants explained that, in investigating these areas, business intelligence teams can achieve a deeper understanding of a system and establish highly valuable relationships with vendors and users. Table 13 includes additional supporting statements that give credibility to the identified themes.

Table 13

Identified Themes and Supporting Statements – System Usage

Identified Theme	Supporting Statements
Collection of data	"In order to have a good, data-driven culture, you have to have good data."
	"I think it starts with gathering data."
	"So, data is only as good as the input, and especially in this industry, everything is being input or manipulated by a human before it is stored in a database. With a lack of a data-driven culture, you frequently get errors that are not easy to filter out or remove from a database and they get written into the history books."
	"Because you've got to know a plan or outline of the consistency that I spoke of, but people doing things the same way."
	"And without a process in place of needing to go here and do it, and 'these are the parameters and guidelines you need to build your companies with,' that data they're entering suffers from inconsistencies."
	"We need to have good data to start with."
Third-party software	"Maybe the external is like different technologies, such as [transportation management software], stuff like that."
Effect of automation	"And as they do that, they become more data-driven, and they probably don't even realize it, because they're using that information, it's going to help make their decisions on a daily basis, to a certain point or we automate as much of it as possible. They believe what the automation is telling them, you know, in the data, or the executives are the same way."
	"I'm resistant to it as much as anyone else is, because you're afraid it will take your job, which is another risk that individuals have to use."
	"How about having people that have more time to work on other things in their jobs?"

Subtheme: Data Governance. A large host of participants discussed the need for instituting data governance procedures that guide the development of new analyses and data-driven systems. Traditionally, these procedures cover the methodologies that drive development processes, data access procedures, and technical procedures. Participants suggested a variety of governance topics, including some related to technical guidelines, the development process, and building a transition plan. Technical guidelines referred to the design policies that promote a consistent structure between deliverables. Development processes were defined as the actions taken to understand the needs of the organization, identify and build solutions to these needs, and deliver products to internal customers. Finally, topics related to the transition plan defined the ways organizations can move toward a culture of data governance and ultimately become data-driven.

Technical guidelines, as defined by participants, govern the design instructions analysts and data scientists should follow to ensure a cohesive, unified feel to deliverables. These guidelines consist of maintaining a data dictionary and identifying a centralized repository for housing data. Participants explained that holding information in a common location, as well as including a metadata layer with dictionary-style entries for each data point, can help organizations maintain the desired consistency between solutions. This is a critical piece of data governance and often applies to technical members of the business intelligence team.

Participants first mentioned a *data dictionary* as being necessary to the long-term viability of data-driven solutions. Data dictionaries include a description of all available data points in a specific repository, as well as information related to dependencies on this data. Dictionaries also include information on the purpose of certain analyses and systems and can be used to identify key users of systems. The purpose of the data dictionary is to document and understand what tools are available to promote understanding and usage of such tools, as well as to prevent the duplication of efforts and introduction of inconsistencies in the analytics solution.

Barua and Mondal (2019) are highly supportive of data dictionaries, explaining that data should be indexed, cataloged, and understood. Boncea et al. (2017) explained that technical maturity is first affected by documentation and that organizations who have robust documentation are often more mature than those who do not. Several researchers discussed the relationship of data dictionaries to data maturity. Cech et al. (2018) built a maturity model wherein the second phase explicitly requires the indexing, documenting, and cataloging of datasets. Prieto-Morales et al. (2015) offered an opposing maturity model but maintains the necessity for defining datasets during the second phase. Building a data dictionary with indexed datasets can be a time-consuming process, but can be invaluable in providing an organization with the understanding needed to effectively create data-driven solutions.

Some participants raised the idea of having a data dictionary to help organizations understand their own systems. Four of 18 participants, or 22%, discussed the data dictionary as a necessary component of a wide business intelligence platform. Participant 13 discussed the need for understanding logic driving analytical solutions so that decision-makers understand the context of the data being provided:

> You can give me the reports all day long, but if I don’t know how the report was set up and the logic that was behind it and how it’s pulling it, how I look at one thing may be entirely different from how the report was set up.

Similarly, Participant 10 explained that individuals must be coached on the origin of analyses so that they understand the importance of properly inputting information:

> You’ve got to educate them what comes from it, and you’ve got to educate them where it comes from, because a lot of people don’t understand that what they’re doing on those computers all day is being written to a database, and that one day down the line you may

> decide that you're going to come up with an AI project or a machine learning project that's all going to stand up on top of that data that they're inputting.

Some participants discussed the need for labels on individual solutions to be consistent system-wide, and called for those labels to be represented responsibly in the data dictionary. Participant 18 discussed the need for well-designed, unique labels: "And every data point has its own nomenclature, so if somebody pulls data and somebody else pulls similar data… guess what, it's the same data. We're not going to pull different solutions just because…" When asked if proper labels on analytical solutions could resolve many of the consistency problems in the organization, Participant 17 responded affirmatively. Although not discussed by a high volume of participants, data dictionaries where resoundingly supported by those who called out their usefulness. These dictionaries allow organizations to understand what items are included in their current environment, as well as provide a location for operators, leaders, and business intelligence teams to understand the nature of data within systems.

The other major component of technical guidelines users covered was the need for *centralized data repositories*. Participants indicated that the organization should have a single location for storing data used for analysis purposes. Organizations should determine how rigid to make data requirements and whether the business wants to prioritize accuracy or speed to market. In most designs, organizations will need some form of a centralized location to store data from all areas of the organization. This data can then be accessed by the wider cross-functional team or potentially others within the organization. Maintaining a centralized location allows for tighter controls over data accuracy, provides non-technical resources with a single location to find data, and simplifies IT infrastructure. Researchers agree that maintaining a centralized, integrated repository is most ideal. Ylijoki and Porras (2016) explained that data warehouses can be used as a tool to generate actionable insights as a single repository for storing data. Cech et al. (2018) explained that maintaining integration of systems and responsibly interconnecting software and datasets forms the third phase of data maturity. The host organization began steering analytics through a single repository in 2017.

Much of the participant involvement with centralized data repositories is born from the perception of decision-makers using the tools. Of the 18 participants in the study, 11 discussed the need for consistency in data and specifically called out the need for possessing a centralized location. Participant 6 discussed the current state of the host organization and explained that businesses should create solutions that span the organization: “Especially in the environment we’re in right now where we’re so separated out into specifics of what people do, applications that are so defined as far as what they do, as opposed to enterprise projects that actually do everything.” In this way, organizations can provide information and insights to multiple groups without using siloed datasets, while allowing groups to reap the benefits of data collection occurring in other parts of the business. Businesses should understand that following this approach and striving for a centralized data repository may be time-consuming. Participant 11 referred to extended timelines within the host organization: “It’s kind of like what we’ve been trying to get done for the last two years with trying to have the one true source.” When projects are consistently extended past expected deadlines, organizations should look at modifying data policies governing the degree to which “centralization” is desired. Similarly, if projects have consistent mistakes, organizations can give the directive to take extra precautions and become more centralized. In the absence of any centralized location of data, decision-makers find unique ways to locate data, usually outside the scope of business intelligence teams. Participant 6 explained that a lack of planning or a lack of execution encourages decision-makers to look in non-indexed and non-approved locations for data: “If you don’t have a good plan up front, and you don’t stay with it, people start to get information from all these different areas.” Providing a centralized data repository is a useful way to provide decision-makers with the largest amount of data possible while easily ensuring that access procedures are followed.

Adopting the aforementioned technical guidelines can help a data-driven team improve the standing of their systems. Instituting data dictionaries can help understand what systems are currently available. Creating centralized data repositories allows business intelligence teams to provide data to the organization responsibly and with the highest possible degree of consistency, although they may take an extended period of time to develop. These improvements allow an organization to grow technical maturity with the ultimate goal of growing data maturity.

One of the most critical processes in a data-driven organization, according to participants, is the process used by business intelligence teams to design, develop, and deploy systems. Participants discussed a variety of stages in this process, notably alluding to agile methodologies. Those interviewed for the study explained that business intelligence teams should also focus on (a) requirements gathering, (b) user involvement, (c) interpretation of data, (d) routine reviews of data, and (e) exception management. According to participants, following these procedures leads to effective development practices and provides checks and balances for ensuring system stability. Observing agile development methodologies and the additional five facets of the development process leads to increasingly mature organizations.

Some participants discussed the need for practicing the principles of *agile development*. This methodology, initially envisioned for use in software development, encourages incremental improvements, continuous delivery, and flexibility in project work. Under these procedures, data-driven teams can provide a minimum viable product and better understand the needs of decision-makers before making a significant effort to deliver potentially unnecessary aspects of a system. Agile methodologies encourage frequent discussions with internal customers. Foster et al. (2015) explained that departmental procedures should be formalized to ensure consistency of solutions and to protect their accuracy and validity. Consistent with the agile framework, Grubljesic and Jaklic (2015) suggested providing fast results with high rates of return; this concept relates to the need for producing a minimum viable product to gain confidence among organizational decision-makers. Cech et al. (2018) promoted this as well, explaining that early victories utilizing minimum viable products are often followed by a high level of confidence from organizational leaders. Finally, Grubljesic and Jaklic (2015) described the need for including decision-makers and users throughout the development of business intelligence tools.

A small number of participants, three of 18, or 17%, alluded to the need for following agile principles in data-driven solution development. These participants primarily discussed the need for heightened flexibility and cooperation among teams typically found in agile methodologies. Participant 6 explained that flexibility in development procedures allows teams to adjust as changes are introduced in the business: “Because if it takes a long time to get somewhere and it’s not flexible enough to move as the business moves, then it’s not a good way.” Participants also discussed the need for user participation at key intervals throughout development. This involves decision-makers putting forth active effort to convey their needs to business intelligence teams, as well as provide intermediate feedback throughout the process. Participant 6 also stated that this time investment is crucial to providing well-designed tools:

> Let’s say you’ve got a project. You need information or assistance from other areas to be able to do your project properly, to understand it properly, but too often, we can’t get

> others to invest the proper amount of time to come up with the information that you really need in order to do an effective job.

Similarly, Participant 11 explained the need for active user participation in the development and validation phases, stating that a lack of active participation results in poor products and frequent unnecessary revisions:

> Kind of like I've been going through on these reports. I'll develop a report, send it over, have them look at it, sometimes they say it's great and then push it to production and they come back and they start asking more questions and then you're two months down the road and there's one version after another. Part of it is our fault because we don't do a good job of holding them accountable to what they originally stated they wanted…

Following the principles of agile methodologies can help prevent these unnecessary inefficiencies. Participants explained that improved flexibility through the development process, combined with active user participation, would be of great benefit when working to provide data-driven solutions to decision-makers.

Several participants discussed the need to place emphasis on *requirements gathering*. This phase of the development process requires business intelligence professionals to discuss needs with decision-makers and understand the goal of new initiatives. Participants explained that this understanding is crucial to providing a useful solution that meets the needs of decision-makers. Perfecting these processes allows organizations to more quickly and effectively provide users with solutions and contributes to the overall trust and understanding necessary to create a data-driven, data-mature environment. Researchers tend to agree with these assertions, with several confirming these needs even within the trucking industry (Chai et al., 2017; Parra-Romero et al., 2017). Garcia-Perez (2018) described the need for business intelligence teams to understand the ways their solutions interact with business processes, explaining that this is necessary to gain trust with decision-makers and provide useful tools and insights. Halaweh and El Massry (2015) explained that business analysts and data scientists should understand how their solutions fit with the overall business context. In doing so, business intelligence professionals can provide the most effective and useful solutions to organizational decision-makers.

Four of 18 participants, or 22%, explained the need for understanding the business requirements conveyed by the requestors of analyses and decision support tools. These participants emphasized the need for strong lines of communication between decision-makers and business intelligence teams. Participants explained that the ultimate goal of this phase of the development process is to understand the goals of business decision-makers and gathering the information needed to provide the most effective solution. Participant 13, an operational manager, highlighted the need for effective communication and ensuring that all aspects of a problem are properly conveyed to the business intelligence team:

> I know how things I would like for them to work, but sometimes being able to communicate that to someone that can generate it in a report, sometimes I wonder if I’m being detailed enough, using the right terminologies… sometimes we think people can read our minds.

Decision support personnel underscored this need as well. Participant 6, responsible for several data-driven technologies in the host organization, explained that to be most effective, business intelligence teams must understand the specific needs of users and the purpose for their requests:

> We have to be able to work with the users and those are probably the biggest questions you can ask whenever you’re creating a report or something for somebody, is, ‘What is

> your goal with this data? What are you trying to do with this data, so I can help you put this data together so it will do exactly what it needs to do.'

Participant 7, discussing the role of understanding from an analyst perspective, explained that for analyses to be most useful, decision-makers and support personnel must be patient and work together to understand the context of an issue and identify potentially relevant details:

> And then also just, and before we even get started on a project, just making sure we're on the same page and not just trying to briefly describe something but actually trying to understand the details and sitting down with him and discussing it. Some of the smaller details that are going to have a big impact on whether it's going to be a report or an analysis. So, I guess patience, and him making the time to follow up on anything he's asking for.

Understanding the context of a problem and the fine details helps analysts and data scientists understand the meaning behind data. Participants were largely in agreement that an early and sometimes ongoing phase in the development lifecycle is understanding the needs and requirements of decision-makers. In doing so, analysts and data scientists can best understand the ways their solutions will affect organizational outcomes and, with this knowledge, can provide more useful tools and insights to operational and strategic decision-makers.

A further need in the development process, and a running theme throughout agile methodologies, trust, and team population and design, is that of *user involvement*. This topic finds relevancy in many different themes, not the least of which is the data governance process. Maintaining user involvement from the beginning stages throughout development and maintenance of systems is a necessary aspect of data-driven processes. Researchers support this assertion, claiming that decision-makers should lend their involvement throughout the development process and the wider governance plan. Mesaros et al. (2016) claimed that business intelligence teams should be carefully constructed, with Grubljesic and Jaklic (2015) adding that decision-makers and end users should be included in such teams. Skyrius et al. (2016) explained that teams should be cross-functional in nature and include business decision-makers where possible. Kulkarni et al. (2017) identified user involvement as an important activity for creating tools that can be widely adopted throughout the organization. Whereas this inclusion has significant and important application to the themes of trust and team design, user involvement is addressed once again to demonstrate its usefulness to providing well-designed systems and useful decision support tools.

Participants frequently discussed the need for user involvement, particularly in regard to the data governance angle. Of the 18 participants in the study, 11, or 61%, discussed the need for involving users to create more accurate and insightful systems and to improve overall system design and stability. Participants frequently explained that decision-makers should be brought into teams as partners and that users should take on a participatory role in the development process. Participant 16 explained that data consumers should be involved in the development process and specifically engaged in helping produce early deliverables: “And then you’ve got to have the consumers of the data helping you build it and helping you produce your quick wins, so that’s key.” Working with decision-makers as partners helps understand their needs and what business intelligence teams can provide to help provide decision support tools. Participant 7 discussed the need for strong communication between business intelligence individuals and organizational decision-makers: “Mainly just communicating with who your data is going to be presented to and then understanding what they need to see on a day-to-day basis to manage their business.” Participant 6 described the potential drawbacks to neglecting user involvement, explaining that developing systems in a vacuum can result in incorrect analyses or unactionable insights:

> You've got to have the users help you to understand what they're after, because in the end, we can create some reports and put the data together, but if we don't have an understanding of their end goal, then we may not put the data together in the right way.

User involvement strongly relates to many previously mentioned concepts, such as gathering requirements, proper collection of data, and fostering trust throughout the organization. From a data governance perspective, building and maintaining relationships with decision-makers and users of new technologies can help improve the accuracy and usefulness of the new systems being designed.

As a fourth topic in the development process of data governance, participants identified the need for regulating the *interpretation of data*. Participants explained that in the post-deployment phase of analytical development, data scientists and analysts should work with internal customers to help interpret the data. A number of participants noted that decision-makers unfamiliar with statistical concepts need additional guidance in understanding the outputs of analytical insights. In this way, business intelligence teams must be adept at providing translation of insights into understandable business objectives. Researchers support this need, generally agreeing that responsible business intelligence professionals should ensure proper interpretation of results (Cekuls, 2015). De Saint Laurent (2018) argued that organizational leaders often have difficulty interpreting statistical and analytical outputs and may introduce statistical fallacies into their interpretation of results. Researchers suggest investing in basic mathematical education for consumers of decision support tools, as well as the need for analysts to work closely with these consumers to properly convey the meaning of results (Cekuls, 2015; de Saint Laurent, 2018).

Participants focused their discussion of interpretation of data on the propensity for decision-makers to project their desires on analyses. Five of 18 participants, or 28%, explained that proper interpretation of data is necessary as a near-final step in the decision-making process. Applying the correct interpretation to the presentation from a data analyst or data scientist is important for proper decision-making. Participants, including two members of the host organization's leadership team, explained that business leaders and decision-makers can sometimes introduce bias into interpretations of data. Participants also explained that decision-makers, even in the absence of bias, may not fully understand the data being presented. Participant 3 explained that decision-makers, and specifically managers, must respect the outcomes of data analyses and not project their desires onto the information: "I think it's how management acquires that data, and how they interpret it. If they analyze the data for what it is, not what they want it to be." This participant went on to explain that faulty interpretations can create long-term issues:

> They are taking that data and interpreting it for what they want it to be, and making decisions off what they think it should be, that can cause long-term problems, versus taking the data and interpreting it for what it is.

Participant 6 likened interpretation of data to the development of a return-on-investment analysis, explaining that individuals can frequently manipulate data to project a different version of reality and that this manipulation should be avoided:

> That's just like anything else, like I said, interpretation of the data, anybody can, just like an ROI, if you like this project and you want this project and you're always thinking about this, you can always come up with ways to show the ROI where this is where it's what we're going to get.

Ensuring proper interpretation of data is an easily-overlooked responsibility of business intelligence. Working with decision-makers to ensure accurate understanding and interpretation can help improve the quality of decisions made based on the data, and can help prevent inaccurate information from being propagated throughout the organization. Participants explained that education and training for users on interpretation of data is necessary as part of the data governance process and identified the need for analysts to work directly with the target decision-makers to help guide interpretation of data.

Participants next discussed the need for *routine reviews of data*. These reviews, according to participants, should take the form of regular check-ins covering the accuracy of data as well as the stability of insights provided to decision-makers. Participants favored this approach due to the dynamic nature of the host organization as well as the statistical need to review data models over time. Researchers did not specifically address the need for routine reviews, although researchers' findings related to the aforementioned themes of user involvement and interpretation of data indicate that these checks are supported. Many participants, 11 of 18 surveyed, or 61%, pledged support for ongoing reviews of data. Several participants noted the dynamic nature of systems within the host organization, explaining that process changes, modifications to the business model, and operator interactions with source systems can influence the validity of data models and insights provided by business intelligence groups. Participant 8 explained that analysts and data scientists should be cautious when gathering data and note that process changes may alter the validity of their findings: "Now, with that, as you gather data, you have to be prepared and understand that the effects of a change in the way that you're doing something will affect the data." Participant 7 likened the need to review data insights to the need to review return-on-investment analyses throughout a project lifecycle: "That's why you always have to go back and revisit ROIs and revisit the analysis to ensure that things haven't changed from the operations." The impact operational processes and user interactions with primary organizational systems can have on business intelligence solutions highlights the need for data analysts and data scientists to maintain reviews with business users. These reviews can reveal potential changes in the organization that may necessitate updates to business intelligence models and insights. Several participants suggested conducting reviews in a cadence over the life of the data model or system. Participant 1 explained that routine reviews, on a set schedule and involving the correct stakeholders, can allow business intelligence practitioners to monitor both interpretation of data and potential changes to solutions:

> Probably a routine review of the data, whether that is… depending on what it is and how frequently it gets updated, monthly reviews, quarterly reviews, with the individuals that are impacted by that data… the individuals and departments that are impacted by changes to processes because of that data. I think it's important to have that regular cadence of making sure that the individuals that are involved understand what the data is and what potentially could change as a result of that data.

In these regular reviews, participants explain that business intelligence teams should review potential changes and ensure that systems are used and interpreted as expected. Furthermore, Participant 9 added that these check-ins should monitor the way users interact with core systems and reviews of the goals of the particular data-driven solution: "Cadence of regular check-ins, regular resets, and goal reviews, and data collection rules, whatever… we have reviews." When analysts and data scientists review business intelligence and decision support systems with organizational decision-makers, they are able to better ensure the continued validity of insights. This activity contributes to overall organizational trust of data-driven systems and drives further adoption of technologies. Conducting reviews of systems helps identify areas of improvement and provide users with a forum to address concerns or opportunities for improvement.

According to participants, organizational decision-makers should not expect business intelligence and decision support systems to behave flawlessly and without error. Just as humans, complex technology systems are prone to mistakes that must be managed. Some participants described a key indicator of progress with regard to implementing and improving data-driven systems in the organization. Two of the 18 participants in the study, or 11%, explained that *exception management* should reveal, to an extent, the benefits of data-driven automation. These participants indicated that, as organizations become more data-driven, error rates should decrease. Although these errors require human intervention, lower error rates and the elimination of human involvement in the remainder of cases is a useful indicator of progress. Participant 10 explained that data-mature organizations should begin to see a decrease in error rates in their core systems:

> I would say error corrections. So, we have an order-to-cash workflow. How many times is data corrected in the system? If we enter a rate to a carrier of a thousand dollars and it makes it through workflow and it his Finance and they have to go in and make a correction… if they do that 10 times day and they only do that one time a day, you're beginning to build data maturity through the organization.

Improving rates of exceptions in databases helps contribute to trust in data-driven initiatives and strengthens data maturity, and allows data scientists to focus on more value-adding activities.

As a component of data governance, the development process behind analysis is a major building block of creating a data-driven culture. In a culture so dependent on the validity of results and an extremely low acceptable margin of error, instituting processes that drive accuracy of outputs is crucial. Participants called out the need for a standardized development process, specifically calling out the adoption of agile methodologies while focusing on (a) gathering requirements properly, (b) involving users in the process, (c) ensuring accurate interpretation of data, (d) conducting routine data reviews, and (e) properly managing exceptions. Figure 5 demonstrates the development lifecycle that should be employed by business intelligence teams. Following these procedures, according to participants, allows business intelligence teams to be most effective and transformative in an organization.

Figure 5

Development Lifecycle

Once organizations and specifically data science teams understand their desired governance process, they may begin to develop a transition plan. Participants explained that this is crucial to execution on the desired strategy. Participants identified three major components of developing a transition plan, including (a) defining current data governance processes, (b) managing change, and (c) conducting process reviews. Following these procedures allows organizations to put governance systems in place to drive data maturity and improve data processes. In this way, organizations can encourage data-driven decision-making throughout their business.

A transition plan to a set of data governance processes involves *defining the current state* of governance procedures. Participants frequently explained that understanding the way existing insights are delivered is important to determining gaps and how the desired future state can be achieved. Farrell (2018) explained that the first step in transitioning is documenting current procedures and identifying the major differences between current and future state. Furthermore, when evaluating current state, business intelligence teams should identify ways to bridge the gaps between the two designs (Farrell, 2018; Stacho et al., 2017). Several participants, seven of 18, or 39%, stated that defining current state is a necessary part of data governance. These participants clearly stated that being aware of the current state of affairs is a necessary part of transitioning to more effective data governance. Participant 5 stated, “First, you have to clearly define your previous state.” Participant 8 opined that data scientists in particular should be familiar with the current and future states: “Identifying as a data scientist where you were, where you’re going, and where you’re at right now are critical.” Participants were clear that business intelligence teams should have an awareness of existing policies and procedures, as well as the technical guidelines, development processes, and desired governance rules going forward. In doing so, analysts and data scientists can best identify a path toward improvement.

Participants next discussed the need for *managing change* in the organization. Instituting data governance procedures requires many individuals within the organization to accept changes, a task that may create animosity between groups. Furthermore, this change requires the codification and adoption of new processes that are intended to protect the stability, availability, and accuracy of decision support tools. Foster et al. (2015) discussed the need for standards and best practices to be instituted within IT organizations to encourage consistency between systems. Ahmadi et al. (2016) explained that processes among the wider organization should support data-driven decision-making, a process that includes data governance. Some participants discussed the need for data-driven teams to properly manage change in the organization. Three of 18 participants, or 17%, specifically called out the need for being diplomatic throughout organizational change. These participants explained that managing change is a key factor in achieving success in transforming data governance procedures. Participant 12 discussed this need in greater detail, arguing that decision-maker acceptance is a determining factor in the success of data governance strategies:

> I think change management is a huge thing for most companies. I think that's probably what contributes a lot to some companies' success or failures. How the personnel is either managing the data or using the end piece of software, how they accept it.

Though business intelligence teams and change agents are ultimately responsible for transforming culture and instituting data governance procedures, organizational users must demonstrate a willingness to change. Participant 8 stated that individuals in the organization should be willing to make changes when necessary: "Change management is key in making sure that you and the individuals that work with you, as your direct reports, are willing to take the steps necessary to make that change in the culture." Without a willing user base, it is difficult for business intelligence teams to effectively institute data governance procedures. Business leaders and decision-makers should be aware that data-governance procedures, while sometimes adding additional bureaucracy, are intended to improve long-term stability and consistency of decision support tools. When this occurs, data analysts and scientists are enabled and empowered to make changes that benefit the business and grow the organization's data maturity.

Once organizations are ready to begin transitioning their data governance processes, participants explained that organizations should undergo thorough *process reviews*. Participants explained that all data processes should be evaluated, including the way operators interact with core systems (referring back to the collection of data) and proper methods of data access. Responsible access of data, according to participants, refers to accessing information in safe and secure ways, as well as accessing stable and consistent sources. Researchers agree with these claims, stating that improper processes can be roadblocks to organizational change (Villamarin-Garcia & Diaz-Pinzon, 2017). Cech et al. (2018) explained that reviewing existing processes can help business intelligence teams make corrections that eliminate roadblocks or catalyze change. Villamarin-Garcia and Diaz-Pinzon (2017) showed that process reviews should occur at all stages of development and culture-building. Identifying faulty processes, especially within the business intelligence team itself, can help teams provide better results to internal customers.

Participants were generally enthusiastic concerning the need to evaluate and review processes. Of the 18 participants, 10, or 56%, explicitly supported the need to review governance procedures and make adjustments where necessary. Several participants championed the use of procedures to govern responsibilities and the methods by which business intelligence teams can establish consistency. Participant 16 described process reviews and modifications as ways to normalize development processes into homogenous methodologies:

> That's a whole other process that would feed into, and so you just have to have discipline really, that's what process is all about. You have processes in place to standardize and make things easier for everybody so everybody understands roles and responsibilities, then you have to have the discipline to follow them and govern them.

Some participants focused their analysis of process reviews on the purpose and need for such reviews. Participant 8 established the need for data governance processes by explaining the volatile nature of data access, especially in larger organizations: "I think there needs to be checks and balances along the way because data can get out of hand." Many participants identified the development process as a particular target for process reviews, explaining that the technical methodologies for developing decision support tools are a major focus of data governance.

Participant 9 explained the need for data governance in the development process, indicating that reviewing and refining processes allow business intelligence teams to act as a cohesive unit rather than a set of individuals:

> And governing it is another area. We’ve got to make sure we are keeping ourselves in check, and not straying and doing our own things. Sometimes we might have a set bunch of numbers and reports we use to run our entire business, but then other people might create their own one-off things, and now we’re no longer following the strategy we put out, and that’s just a break in the whole process.

Participant 8 reiterated the need for consistency in development, demonstrating that a lack of data governance and, in particular, process reviews leads to inconsistencies that create confusion and erode trust: “I think there would have to be a consistency with how things are done, so you don’t have someone programming it a certain way and someone not, but there has to be that consistency.” Process reviews in data governance cover tasks through and beyond the delivery of decision support solutions. Participant 6 explained that delivery processes, platforms, and formats should be standardized across the organization: “We’ve got to have a good philosophy about how we’re going to delivery it, and people have to buy in to how it gets delivered and how it gets calculated.” Because of the great need for consistency in data-driven solutions and its strong relationship to trust in data, participants agreed that process reviews are needed. These reviews help maintain consistency and responsibility in data access, manipulation, and analysis.

The transition plan, as part of a data governance strategy, allows business intelligence teams to drive the remainder of the organization toward standard processes intended to improve system stability, consistency, and ultimately data maturity. Participants described several aspects of transition plans, including (a) understanding current state, (b) managing change throughout the organization, and (c) reviewing processes to ensure adherence to data governance plans. Instituting transition plans allows the growth of data maturity and strengthens decision support tools and decision-makers' abilities to make better, more informed decisions.

Data governance comprises the methodologies used to develop data-driven solutions, including interactions with users, interactions with computing systems, and interactions with data. Placing governance around data access, development, and dissemination allows business intelligence teams to ensure a certain degree of consistency and stability in their products. Participants focused first on the technical aspects of data governance, explaining that centralized data repositories would be necessary to create a cohesive platform. Participants also discussed the need for governing the development process, ranging from gathering requirements to the delivery and review of data-driven solutions. Finally, participants discussed the ways organizations can institute transition plans intended to move the business toward data governance processes. These processes allow the organization to grow data maturity and provide better services and decision support tools to decision-makers. Table 14 provides additional supporting statements regarding the data governance themes identified by participants.

Table 14

Identified Themes and Supporting Statements – Data Governance

Identified Theme	Supporting Statements
Centralized data repositories	"We've got several different places where the same data comes from."
	"There are so many different sources that no one is comfortable with."
	"Also maybe having one source of whatever it may be…"
	"They had a central location where all the data was stored."

	"I would say number one, it having… all reports saying the same thing."
	"That's where we struggle right now, we don't have everything coming from the data lake. So, we've still got that disparity in our reporting."
	"We've got to score off of the same scoreboard and live by it."
	"But we need to plug Power BI into one source of the truth, and right now we're working on two sources."
Requirements gathering	"You have to work with your business owners because you have to understand what their needs are."
User involvement	"Let's say you've got a project, you need information or assistance from other areas to be able to do your project properly, to understand it properly… but too often, we can't get others to invest the proper amount of time to come up with the information that you really need in order to do an effective job."
	"You have to work with your business owners because you have to understand what their needs are."
	"I think it's engaging the stakeholders to understand what they need to run their business."
	"I think… this is very similar to what you do in any process improvement project, you bring stakeholders from every department that's affect by the process."
Interpretation of data	"Try not to inject any kind of… I guess interpreting the data for what it is."
	"I think it starts with education. So, we're in an industry where you have a lot of… if you take our entire employee base, you take drivers, terminal employees, brokers, all the way through… there are a lot of people there that have never experienced or never been through education of data. They've never been through a statistics class in college. They've never been taught how it can be used to your advantage and how it can be used to develop a business. So, you've got to teach them first."
	"The problem we have as operators… we're like deer hunters. Everything we see through the scope is a deer. And if it isn't a deer, we want it to look like a deer. So, we tend to tell pretty little stories and leave out the big part of the narrative that tells a different story."

Routine reviews of data	"They were always in communication with the people that were using the data and also were getting feedback on how that data was being used." "They need to constantly reevaluate what metrics are driving their company." "I think that also in order to be able to know for sure, you've got to go back, and you've always got to circle back, and check back in, I mean, we don't do that. We don't have check-ins for reports. We have so many reports just out there that people built that no longer work here, that are still running, but it goes back to resource availability." "I think you probably need to do some checks and balances. Go out there and take sample sizes of your data and analyze it for accuracy." "I think it just has to be audited or looked at, that something else within that organization hasn't changed that has… that we have kept the reporting and stuff updated." "I think we need to make sure from an IT standpoint that we're always following up. And especially, trying to get feedback and trying to improve on it, and deal with it."
Exception management	"Fixing inefficiencies on that low of a level throughout the organization."
Process review	"You have to have the systems and technology in order to get to that point, but then also you have to have good processes in place, that are documented so that there's no confusion on how you enter data. You want a consistent process in terms of what steps you take, whether it is building a load or… you want there to be a documented process and that process should be the same for everyone […] The data should stay the same regardless of who is entering it." "If you don't have a good plan up front, and you don't stay with it, people start to get information from all these different areas." "Well, it allows us to have checks and balances on what we're doing, and ways to track how we're doing, and have methodologies that we follow, and keep consistencies, and I think above all checks and balances." "There kind of needs to be a more formalized process. They request something, needs to be a formalized request. We develop it, send it

> back to them for approval, there needs to be a formalized acceptance, then it gets pushed into production."
>
> "I think if I was just saying based on experience with USA Truck, my experience would be that I think our lack of processes in certain job functions and roles, I think that really hurts our ability to go toward more of this data-driven culture."

Subtheme: Measuring Success. In any organizational initiative, and especially throughout data-driven endeavors, businesses must be able to measure progress and determine levels of success. Participants discussed a host of concepts describing the ways organizations can measure their data maturity, as well as substitutes for quantifiable metrics. Participants explained that data are a critical component of organizational operations and argued that business results can be good indicators of success. According to participants, financial results, in addition to operational metrics and other high-level measures, can be used to simulate data maturity and provide insight into the organization's culture. Finally, organizations can look to data-driven deliverables to determine their rate of task completion.

To understand the ways overall organizational results can be used to simulate measures for data maturity and adoption of culture, participants explain that, because of the *criticality of data*, decision support tools are pervasive entities that have a strong influence over the remainder of the business. Researchers support this position, explaining that data-driven cultures frequently experience gains in performance at the time of adoption (Bajari et al., 2019; Muller et al., 2018; Popovic et al., 2018). Lehrer et al. (2018) supported the idea that business intelligence improves both financial and non-financial metrics. This indicates that, as participants stated, the widespread influence of data can strongly impact countless organizational key performance indicators. Participants argued that this strong link allows organizations to simulate culture using more easily-measurable variables. All 18 participants, or 100%, claimed that data are a critical asset of the business and should not be ignored. To illustrate this point, participants described scenarios in which an organization refused to grow their data maturity. Participant 11 explained that the sorts of organizations are unable to become proactive and solve issues:

> Then you're just going to be constantly reacting. You won't be able to plan for anything long-term. You won't be looking at any kinds of trends or anything of that nature. You're just reacting to things as they happen. You don't learn from past mistakes. You won't be able to spot an opportunity that might be coming up.

Participants highlighted the potential for organizations to fail when refusing to adopt data-driven technologies. Participant 10 explained that a lack of data insights prevents organizations from knowing their current place and how to grow: "You can't see enough to improve, and if you can't improve in any industry, you'll become irrelevant." Participant 4 described such a scenario in more extreme terms, discussing the possibility of losing the business if culture is allowed to stagnate:

> The biggest risk of not doing it is, number one, you don't improve, and number two, you have a culture that just becomes stagnant and you'll regress. And rather than grow, you shrink, and worst-case scenario, you go out of business.

Participant 16 concurred, stating that organizations who do not measure their business through data become satisfied with mediocrity and lose decision-making capabilities:

> I think what gets measured gets managed. So, if you're not data-driven you're likely not measuring your performance. So, bad results, mediocrity. That's the results, that's the risk of not being data-driven, which is horrible. Everybody wants to compete. The worst that would happen is you go out of business due to your lack of performance, or lack of ability to be nimble and draw conclusions.

Some participants explained that data are critical to understanding outstanding issues in the organization. Participant 18 described the effect of a lack of data in a business, explaining that without information, employees would not know what needs to be done or what potential solutions might be:

> Mayhem. We would literally have people using mythological problems and mythological answers to the problems. Just wouldn't have any clue… be like trying to cross the ocean without a compass and a map. You can't drive a car without data. You have to know how fast you're going, what direction you're going, which way the wheel is turning… that's data. And so, the result wouldn't be good at all.

Acknowledging the criticality of data to the organization enables businesses to model business maturity using organizational metrics. Furthermore, in acknowledging data analysis as a critical element of business, leaders signal their support to the organization. Businesses should, according to participants, recognize the importance of data to their organization and be willing to adopt data-driven practices. This adoption allows businesses to become more productive and efficient, gains that should be evident in top-level metrics.

Several participants discussed the ways in which data-driven initiatives impact top-level financial results, as well as the ways top-level metrics can indicate, to a degree, the success of a data-driven culture transformation. Researchers frequently agree with this finding, with many discussing the effect of data analytics on firm performance. Bajari et al. (2019), Muller et al. (2018), and Popovic et al. (2018) explained that the adoption of data-driven technologies consistently has a positive effect on an organization's performance. Muller et al. (2018) specifically stated that simply actively engaging in data-driven decision-making leads to an average of 3% to 7% increases in productivity. Popovic et al. (2018) showed that advanced data science initiatives improve performance when enabled by IT capabilities. Heller (2019) explained that even at the individual level, business intelligence helps in making improvements. Bajari et al. (2019) argued that storing and analyzing large datasets improves organizational performance, though they explain that at some point this reaches diminishing returns. Researchers consistently argue that data maturity leads to improved performance, although they do not state, as participants do, that the converse, that improved performance is always attributable to data maturity, is true. Participants indicated that data maturity can be measured by organizational success, though some participants acknowledged that there may be other confounding variables.

In terms of financial results, participants first stated that *culture affects revenue*, not limiting this claim to only a data-driven culture. Five participants of 18, or 28%, explained that during and after a cultural transformation, if the culture is positively received, revenue is eventually improved. Participant 7 explained that a well-designed and well-implemented culture should impact financial performance: “I think that at the end of the day, if you choose the right culture and choose the right direction, you’ll see it eventually in your finances.” Participants referred to both increases in revenue and reductions in cost. Participant 15 expanded the claim of culture’s impact on revenue to expenses as well: “Number one… the performance of the business. You want to see either an increase in revenue, increase in profit. Same thing on the cost side, hopefully you’ll find opportunities to reduce or eliminate cost.” Participants warned that positive effects in revenue and costs can take time and that organizations should not expect to see returns for at least several quarters or even years. Participant 11 explained that results should appear incrementally over several periods, both in financial and non-financial metrics:

> Well, I think part of it is, you can look and see from a business perspective, period over period. Have we seen an increase in revenue, or an increase in seated trucks, or decrease in accidents? So, there's empirical data that can support that.

Participant 4 described the long-term nature of culture transformations and subsequent impacts on financial metrics, explaining that effects may not be realized for many years: "Maybe within the next two or three years you could probably look back and say, 'Okay, now we're starting to see results,' because that culture is fully implemented." Participants strongly suggested that positive changes to culture result in positive effects on financial data. These changes must be well-received and adopted by the organization, effects may not be observable for many years, and effects may never be completely attributable to a culture transformation. Nevertheless, participants believed that culture can have a strong, noticeable impact on the revenue and costs in an organization.

In measuring cultural effects on financial results, participants overwhelmingly stated that business intelligence teams should *demonstrate improvement* and link data-driven projects to firm performance. Of the 18 participants in the study, 16, or 89%, stated that identifying key areas of improvement targeted by data-driven solutions, followed by measuring these performance indicators, can help demonstrate the positive impacts of decision support tools. Participants described growth in several different areas as being indicative of a successful culture transformation, including productivity, customer and employee experience, and maturity. Participant 14 stated that growth in productivity, as a result of data-driven decision-making, is a determining factor in whether or not a culture transformation was successful:

> Well, you look at the growth of your company, and how efficient your employees are, and their productivity. Because if you make decisions based on data, and you see that the

> growth is there. And your employees are more productive because of that. That's when I'd say you'd be winning.

Some participants identified improvements in the employee and customer experience as indicators of success. Participant 10 described that these improvements in experience are the key purpose of becoming data-driven and that demonstrating gains in these areas can help provide evidence of a successful transformation: "You're doing it to improve the company and improve the experiences of the customers and improve the experiences of the employees. So, they've got to see the fruits of that." Finally, participants recognized data maturity as an indicator of success. Participant 16 suggested evaluating the state of an organization's data maturity at regular intervals to determine if the organization is progressing through the stages of maturity as expected:

> I think you've got to go up the maturity level. So, are we using data for reporting? Are we looking at lag measures? Are we looking at lead measures? Are we drawing insights? Are we able to take actions on those? And then, are we able to automate? I would say, if you see a progression going up that stair-step, that's a good way to measure your maturity level.

Participants argued that in demonstrating improvement in key areas, business intelligence teams can show the organization that efforts to become more data-driven are being realized. This is a necessary way to receive continued support from the organization and to understand what potential adjustments in culture or strategy need to be made.

A significant number of participants called for understanding *performance as a result of maturity*. This call specifically highlights the need to understand how performance is impacted by maturity. Of the participants in the study, 12 of 18, or 67%, explained that data-driven organizations should work to identify specific ways that becoming data-mature has impacted firm performance. Participant 10 identifies the importance of this connection, explaining that profit can be affected by many factors other than data maturity: “I guess an ultimate measure of data-driven culture is the end result. Is the end result getting better? I don’t know if I would measure it in terms of profit because there’s other things that control that.” Some participants indicated that, to measure success, key metrics should be narrowed to those that are a direct result of data-driven initiatives. Participant 16 connected continuous improvement efforts to overall organizational performance, implying that metrics tied to these continuous improvement efforts can be designated as proxies for measuring data maturity: “If you’re able to use that data to feed continuous improvement efforts, that contributes to your ability to improve performance overall.” Participant 18 affirmed this statement, explaining that metrics positively changing as a direct result of data-driven initiatives can help organizations identify which projects are finding success and which are not: “When all that comes into play and you see results change, that’s how you know when it’s been successful.” Identifying measurable financial and non-financial metrics that are a direct result of data-driven efforts can help demonstrate to organizations the positive impact of a new culture. Participants explained that understanding these levers and being able to showcase direct ties between business intelligence projects and measurable success indicators provides data scientists with credibility and encourages organizations to continue investing in data-driven initiatives.

Measurable key performance indicators are not the only way to identify success in a data-driven culture transformation. Participants identified various indicators of success that, while harder to measure empirically, should be observable using more anecdotal methods. Researchers agree with this sentiment, with many stating that data-driven initiatives improve the decisiveness and quality of decisions being made by organizational consumers (Arghir et al., 2019; Brynjolfsson & McElheran, 2016; Nykanen et al., 2016). Lehrer et al. (2018) identified several other areas of improvement as well, including personalization of service, improved purchasing agreements with vendors, and perceived value of products and services offered.

Some participants discussed the way *culture affects retention*. Participants explained that despite the likelihood of positive cultures to affect positive change, culture transformations will inevitably lead to some degree of increased turnover. This can be a form of functional turnover, in which a small degree of turnover is acceptable so that companies may cultivate a cohesive team with common values. Three participants of 18, or 17%, highlighted this possibility. Participants were largely supportive of a degree of functional turnover. Participant 4 explained that changes to processes frequently result in personnel changes: “Once they implemented the process and it started to work its way through the organization, obviously you’re going to have people who buck the system. You’re going to have some turnover.” This participant opined that this effect was observable during a recent culture transformation at the host organization: “When we implemented our culture here, our values here… I’ve noticed a lot of changes, and I’ve noticed some people didn’t like it, so they left.” Despite the positive intentions of implementing a data-driven culture, such a design often results in process changes. Participant 5 discussed this necessity and the effect it may have on employee satisfaction and turnover:

> I think the downside is, sometimes you don’t realize what actually drives your company until you do the project and you want to go data-driven, and it’s a good thing you find out what’s actually making the change, but sometimes it takes some big changes that people don’t like.

A small degree of functional turnover, while unfortunate and inevitable, is necessary for adopting a culture that supports data-driven decision-making. According to participants, organizations should almost consider this a form of validation, so long as turnover does not become dysfunctional or continue to grow. After the implementation of a new culture, and assuming the culture was properly designed and adopted, organizations should expect to see turnover stabilize and possibly improve.

A corollary of turnover is the *effect on morale* that culture transformations may have. Similar to the acceptability of functional turnover, participants claimed that organizations should expect to observe fluctuations in morale with eventually stabilization and improvement in aggregate. Participants warned that morale could suffer in a data-driven environment, but ultimately employee satisfaction should improve over time. Eight participants of the 18 in the study, or 44%, described the ways morale could improve in an organization and how these improvements can be used to measure the success of a data-driven culture transformation. Participant 3 cautioned that becoming too data-driven could cause a lack of focus on soft issues and the needs of employees as humans:

> You could lose focus on employee morale. Could cause high turnover because you're so focused on that end result or goal that you're not maintaining relations with the staff. Could be driving a culture of all these numbers and the negative effect is you could really put the team down if they have a slump.

Despite these warnings, most participants explained that morale should improve and can be a measure of employee acceptance of a new culture and the data-driven nature of organizational decision-making. Participant 9 explained that observing morale can help leaders and change agents understand the effect their work is having on the organization: "I would say morale, because people might kind of forget about it, that the morale in your day-to-day in what you have to do, morale might itself be an indicator of how things are improving." Participant 13 stated that morale may be observable beyond simple employee satisfaction or happiness, arguing that morale can refer to employee engagement and enthusiasm for their work and for decision support tools: "And probably even eagerness of the team. They're just not satisfied with hitting the results, now what can we do to get even better than this?" Participant 15 also discussed employee engagement, offering a methodology for quantifying the morale of an organization: "And then employee satisfaction. If employees are able to do their job more efficiently, you should see that in your employee engagement surveys." The effects on turnover and morale are a useful way beyond strictly quantifiable metrics to measure the success of a culture transformation and the maturity of an organization with regard to its data. Businesses should carefully monitor the impact on these measures so that adjustments can be made if turnover becomes dysfunctional or if morale becomes toxic. Ultimately, beyond a possible initial period of unsteadiness, participants explained that both of these metrics should improve.

Some participants floated the possibility of using deliverable completion and formalized project plans to identify their organization's position on the data maturity curve. Participants stated that executing on their plans is a difficult but key component of success. These participants explained that following through and delivering items believed to improve data maturity can help provide organizational leaders and decision-makers with the composure to continue funding of data-driven initiatives. Cech et al. (2018) and Grubljesic and Jaklic (2015) supported this claim, explaining that the completion of key deliverables is an indicator of success that pushes leaders to trust business intelligence teams. Four participants of 18, or 22%, mentioned *deliverable-based progress* as an indicator of the success of data-driven processes.

Participant 9 warned that business intelligence teams should pay attention to the execution of their plans and that a lack of execution can lead to failure:

> We need to make sure that we actually get the things done… the execution. We need to follow through to the end, we don't just think it and try to do it and get partially there, we actually have to do it.

Several participants highlighted the usefulness of maintaining formalized project plans. In this way, business intelligence teams can demonstrate the completion of key deliverables and identify organizational improvements that have come from these achievements. Participant 14 recommended using a formal plan and conducting regular checks to promote progress: "Definitely would have to have a project plan, with dates and goals, and of course, you would have weekly or monthly project meetings with all your team members, making sure everybody is on track." Participant 16 corroborated this account, explaining that using a formal project plan encourages execution and adherence to goals: "You put a project plan in place, you start executing on your project plan. It's got your deliverables in it. That's the other way. The most tactical way of measuring it." Identifying completed tasks and communicating these throughout the business demonstrates a degree of success and, at a minimum, progress on data-driven initiatives. According to participants, keeping a record of completed tasks helps recognize areas of improvement that can then be measured to demonstrate the effect of data-driven tasks on the organization.

As a final topic of the design of work processes, measuring success provides an avenue for data-driven teams to demonstrate their contribution to the organization and obtain feedback to help improve the team's output. Participants identified several ways to measure progress and determine impact on the organization. By establishing data as a critical part of all decision-making throughout the business, participants explained that progress could be measured by superficially identifying trends at the highest levels of the organization. Participants encouraged business intelligence teams and organizational leaders to tie data-driven initiatives to the specific metrics that were intended to be affected. In doing so, organizations can track the progress of data-driven teams at a more accurate level. Additionally, businesses can look to anecdotal accounts of organizational morale to measure progress from a cultural perspective. Furthermore, identifying key deliverables and measuring progress can help demonstrate team progress. In these ways, organizational leaders can best track the transformation of culture into a data-driven environment, as well as the specific metrics and decisions targeted for improvement by the business intelligence team. Table 15 provides additional supporting statements behind the themes identified pertaining to the measurement of success of data-driven initiatives.

Table 15

Identified Themes and Supporting Statements – Measuring Success

Identified Theme	Supporting Statements
Criticality of data	"I don't know how anybody could function without it."
	"You could make a decision, go out of business, and then no one has a job."
	"It could cause a lot of uncertainty. You don't know what state you're in, how well you've been doing, just walking down the road but where do you turn off at? Where are you going? Nobody knows."
	"If you're not using the data, then you're assuming what's driving your business, and that can be very dangerous because your decisions may not be having the impact that you're expecting."
	"I think the bad is, you make long-term decisions that aren't supported by data, and they end up ruining a company in some ways. Just making more informed decisions I guess is the answer."
	"Not improving. Not improving ourselves in what we do in our day-to-day jobs. Having no visibility to what we're doing. We're just

	dabbling around with no idea of what is making any impact, definitely for the reporting structure of having a way to gauge performance… people's performance, company performance, executive performance, even to… if you have shareholders or people at that level want to know our performance and you have to know how to show that."
	"You miss reality. If you think about what goes on in just our business alone, we're not a company like Walmart or Amazon. We're nowhere near that size. But we still have, between asset and brokerage, let's call it 3000 trucks on the road at any one time. You can't gut instinct that. You can't pattern that in your head, you can't pattern that on Excel. You can't just have a hunch."
	"Oh, complacency. I don't think that you would, you'd have the complacency, you wouldn't have a drive to improve. You would get so far behind in the technology world."
	"It's really easy to think that you have a feel for the way things are going, but sometimes your gut feelings are incorrect, and so it's always good to back that up with data so that you can make intelligence decisions on a variety of different things, whether it be on performance, business production, cost savings, you always want to have hard evidence before you make decisions on those things."
Demonstrate improvement	"Maybe some goals have been set that the company is trying to reach and those goals could be obviously number-driven, but if you have complete buy-in, you could be really close to that goal or achieve or exceed that goal."
	"I think once you set those processes and that culture of accountability and continue this process then I think over time you'll start to yield results."
	"Well, you have to have a starting point and you have to have some important metrics and before… if you're not data-driven in the beginning, when you initially start, you're going to have to get that baseline piece of data, and do your analysis, become data-driven, and then compare."
	"People's performance, depending on how we measure it, would be a way to tell if we are succeeding."
	"I think it goes back to, 'Here's some of our hurdles. Here's some things we can do to improve it,' so they can see progress, or see the improvement."

Effect on morale	"How do we measure if we have a good culture or a bad culture? You can look at if employees are leaving or staying… well, they might be leaving or staying for different reasons. We could pay people a dollar a year and we could have the greatest culture but people would leave."
Deliverable-based progress	"This is where I would say… when you can use programs like Four Disciplines of Execution that rely on data to drive… whether it's hand-collected or created by some process or platform in your systems, the measurements that show process and the measurements that drive the activities and results…"

Relationship of Themes/Patterns to Research Questions

The process by which businesses design and implement a culture of data-driven decision-making is a complicated, sprawling procedure that takes time and spans entire organizations. Transforming a culture requires the participation of individuals at all levels and in all areas of the business. The findings indicate that such a culture requires a tremendous amount of trust in fellow employees, technological systems, and organizational processes. Transforming a culture into one that support data-driven decision-making requires teamwork and the support of business intelligence teams. Participants in the study also identified a need for heavy reliance on processes to govern interactions with data and computer systems, as well as the development of decision support tools. These findings serve to provide evidence in support of investigating the research questions and to satisfy the needs identified in the problem statement.

The problem this study addressed is the difficulty organizations have in designing and implementing data-driven cultures, even when considering their advanced technical capabilities (Bogdan & Lungescu, 2018; Galbraith, 2014; Grover et al., 2018; Olufemi, 2019). Olufemi (2019) also noted the difficulty in transforming culture, while Galbraith (2014) showed that leaders often are unable to support data-driven decision-making due to the implications it has on their own decision-making power. These findings served to inform the primary research questions of the study. To investigate these questions, 18 interviews were conducted with members of a medium-sized transportation company.

Participants identified several overarching themes along with various subthemes that serve to provide insight into the research questions. Major themes included (a) trust and data maturity, (b) design of culture and teams, and (c) design of work processes. The first theme, focused on trust and data maturity, provided insight into buy-in to technical solutions and the trust decision-makers place in technology, as well as the persuasive tactics data analysts and data scientists must employ to influence decision-makers to adopt data-driven techniques at the micro-decision level. The second theme, focused around the design of culture and teams, gave information related to the ways organizations should (a) design a culture of teamwork, (b) design and populate business intelligence teams, and (c) transform cultures into those that support data-driven decision-making. The third theme that emerged throughout the field study, centered on the design of work processes, encouraged practitioners to adopt process-driven policies for (a) general decision-making, (b) goal-setting and project prioritization, (c) team management, (d) project management, (e) system interactions, (f) data governance, and (g) measuring success.

Three primary research questions directed interviews with participants. All questions included in the interview guide were intended to help provide insight into one or more of the three primary research questions. The findings of the study are organized into various themes and patterns that in turn inform understandings of these questions. The three research questions that directed the study are:

1. What constitutes a data-driven culture?
2. What actions can organizations take to institute a data-driven culture?

3. How can business strategists persuade leaders to turn over a degree of decision-making power?

Research Question 1. The first research question, asking participants to define the components of a data-driven culture, attempts to understand the individual parts that make up an environment supportive of data-driven decision-making. Participants defined a host of components that comprised parts of all three major themes within the study's findings. In response to the question of what makes up a data-driven culture, participants tended to agree that a data-driven culture is primarily the result of improvements to data maturity. Data maturity represents the organization's relationship with data and decision-making processes. When discussing the components of data maturity, participants often pointed to (a) trust, (b) a culture of teamwork, (c) the existence and population of a business intelligence team, and (d) adoption of processes that support data-driven decision-making. Organizations that possess these qualities, according to participants, are often data-driven and are able to reap the benefits that business intelligence offers.

In a data-driven culture, individuals within a business have faith in their data and trust the insights that are provided by decision support tools. Of the 18 participants in the study, 16, or 89%, identified trust as a major component of a data-driven culture. Trustworthy data are a required component of becoming data-driven, as an inaccurate or unstable set of insights erodes organizational support for these initiatives. Participants identified six components of trust in data, with (a) 16 participants discussing accuracy, (b) 11 calling out consistency, (c) 12 supporting availability, (d) six mentioning actionability, (e) 12 identifying integrity, and (f) four discussing robustness of data. Possessing datasets with these qualities, according to participants, provides trust in data, which in turn is a major building block of a data-driven culture.

Participants also identified a culture of teamwork as a critical component of becoming data-driven. Creating such an environment leads to various positive outcomes that participants say are required components of a data-driven culture. Throughout the study, several components of such an environment were revealed, with (a) four participants identifying accountability, (b) two specifying a culture of service, (c) two mentioning a healthy work environment, (d) three arguing for celebration of achievements, and (e) five participants imploring employees to understand their own contributions to the business. Additionally, in a data-driven environment, 11 participants, or 61%, state that decision-makers are involved in the development and delivery of data-driven decision support tools.

Many participants expressed opinions about team design for data-driven initiatives. The majority of participants, 13 of 18, or 72%, explained that teams should be cross-functional in nature and include representatives from information technology and analyst groups. Though some participants stated that teams should be IT-driven or analyst-driven, the majority agreed that a mixture of both allowed each group to bring their unique skills and contribute in a meaningful way to the work of the full team. Several participants suggested that teams also consist of organizational stakeholders and members of operational groups. Ultimately, participants explained that a data-driven culture consists of a team of diverse individuals with a wide range of skills. These attributes include technical, business, soft, and leadership skills that are, in some form, represented.

Finally, participants identified process adoption as a critical component of a data-driven culture. Organizations that are data-driven, participants noted, adhere to a number of processes that guide and inform their operations with regard to decision support tool production and consumption. In following defined processes, organizations can maintain a degree of consistency and stability in data-driven solutions. Nine participants, or 50%, discussed the use of data in operational and strategic decision models. Regarding the production of data-driven solutions, participants identified the project prioritization process as being critical, with 10 participants, or 56%, stating that this should be a collaborative effort, and 11, or 61%, favoring a top-down approach. Of the 18 participants, 13, or 72%, stated that projects should be prioritized based on financial impact, while 10, or 56%, promoted a gap-driven approach. Furthermore, participants indicated that data-driven organizations make use of data governance processes such as technical guidelines and standard development procedures. These processes, taken as a whole, support data-driven initiatives and are a critical component of a data-driven culture.

The components of a data-driven culture and data maturity, as specified by participants, can be somewhat linked to the conceptual framework developed by Cech et al. (2018) and the definitions provided by Cech et al. (2018), Chen and Nath (2018), and Farah (2017). Under the framework of Cech et al. (2018), data-driven cultures consisted of technical guidelines, business processes, and specific team designs. This framework does not include mentions of the importance of trust in a data-driven culture. Conversely, participants did not often discuss the most advanced forms of data maturity identified by Cech et al. (2018), which included adoption of predictive and prescriptive statistics. As defined by Cech et al. (2018), Chen and Nath (2018), and Farah (2017), data maturity refers to the ability of businesses to collect, store, manipulate, and report data insights, in addition to their ability to institute processes in support of data-driven decision-making. Under this definition, participants and researchers are highly aligned in their support of process-driven environments as well as the skillsets required on teams, although researchers did not call special attention to the need for teamwork. Furthermore, once again, participants identified trust as a necessary component of a data-driven culture, though this was not discussed by researchers.

In answering the first research question, aimed at identifying the components of a data-driven culture, participants provided many useful parts that represent all three of the major themes of the study. Participants frequently discussed the need to improve data maturity, which is itself made up of several components. Participants generally agreed that for organizations to improve data maturity and, therefore, data-driven decision-making, they must possess (a) trust in data, (b) a strong team culture, (c) a trained and skillful business intelligence team, and (d) the willingness to adopt new processes that support both the production and consumption of decision support tools. Participants resoundingly agreed that these four elements comprise a data-driven culture, significantly overlapping with researchers. One of the most important topics for consideration, trust, was a surprising discovery not previously mentioned in the conceptual framework or existing definitions of data maturity.

Research Question 2. The second research question seeks to identify the specific actions organizations can take to build a data-driven culture. As opposed to the first research question, which was intended to understand the components of a data-driven culture, this question works to recognize the transition plans and transformations that must be made, at a high level, throughout an organization to achieve a data-driven environment. This question specifically refers to culture and acceptance company-wide at a macro level; topics related to micro-decisions at the individual level are a focus of the third research question. Participants identified a number of activities in which businesses can participate to usher in a culture of data-driven decision-making. Participants also described methodologies leaders and business intelligence teams can utilize to transition to their desired culture.

Participants identified three major actions organizations can take to institute a data-driven culture within their own business. Those surveyed in the study first noted seven major ways to transform company culture. Participants also discussed the need for a data-driven cross-functional team made up of individuals from various parts of the business, specifically calling out the need for teams to adopt teamwork and address several important considerations. Finally, participants identified methodologies for transitioning processes into a cohesive set of policies that support data governance efforts. Following the steps recommended in each of these three items, participants claimed, can help an organization transform its culture into one of data-driven decision-making.

To answer the question of what actions an organization must take to institute a data-driven culture, the question of how to transform culture must first be asked. Participants established a framework of seven activities business must complete to transform culture. Leaders should work to define the desired culture and determine the core values held by the organization as a whole. Change agents must then be appointed and begin methodically transforming culture by executing tasks included in the strategic plan. Throughout the process, organizations must maintain an executive sponsor or project champion that provides regular and public backing to the culture transformation initiative. Change agents and leaders must maintain consistent messaging to provide employees with a coherent plan. Organizations must make training and education in cultural ideals available to employees to allow the transfer of knowledge about such topics. Finally, businesses should remain diligent in the pursuit of a culture transformation and observe continuous improvement practices that strengthen culture and organizational performance. Following these guidelines, participants collectively argued, allows a company to modify and transform their culture. Once organizations have defined their culture, they may begin to methodically execute the tasks necessary to implement such a culture.

Participants explained that companies must have the right personnel and team structures in place to support a data-driven culture. Organizations must first have a diverse cross-functional team defined and populated with the proper individuals, then create a supportive, collaborative environment in which the team can grow and thrive. A majority of participants, 13 of 18, or 72%, advocated for the use of cross-functional teams comprised of both IT and analyst representatives. Half of the participants, or nine of 18, suggested engaging with consultants to provide business and technical advice. Participants stated that in addition to defining a cross-functional team, organizations should create an environment of teamwork to provide business intelligence teams with their best chance at effectiveness. This environment includes (a) accountability, (b) servant leadership, (c) a trustworthy atmosphere, (d) employee recognition, and (e) valuing the contributions of all team members. Organizations should look for ways to grow these qualities in their business, especially with regard to data-driven cross-functional teams. This allows companies to develop a highly effective team that works to support data-driven endeavors.

Finally, participants identified the creation and deployment of data governance processes. These processes, participants explained, are intended to improve engagements with business decision-makers and to grow trust and data maturity within the organization. This relationship and these procedures facilitate the adoption of a culture of data-driven decision-making. Participants described several processes that should be implemented, including processes governing technical guidelines, development procedures, and guidelines for working with decision-makers. Specific to the aim of this research question, participants explained the process by which organizations can transition their existing processes into those that support data-driven decision-making. Participants largely supported a three-phased plan involving (a) defining the current state, (b) managing organizational change, and (c) reviewing existing processes and making adjustments where necessary. Defining the current state, according to seven of 18 participants, or 39%, allows change agents and leaders to understand the existing set of data governance procedures. According to three participants (17%), these individuals should then prepare the organization for change and make these adjustments in a responsible way that does not negatively impact turnover or morale in a major way. Finally, organizations should review their existing processes and make modifications where appropriate, according to 10 of 18 participants (56%). Reviewing such processes allows data-driven cross-functional teams to engage decision-makers in data-driven technologies and helps improve trust within the organization. Improvements in processes contribute to greater system consistency and stability, which in turn improve decision-makers familiarity and trust in decision support tools. This improvement in engagement and trust contributes to the creation of a data-driven environment and is thus an important part of the transformation to a culture of data-driven decision-making.

The conceptual framework provided by Cech et al. (2018) provided a hierarchy of capabilities that organizations must possess to improve their data maturity. Participant responses largely remained consistent with this hierarchy. Many individuals identified the need for transforming culture, building data repositories, acquiring innovative technical skills, and instituting process-driven management, each of which are qualities of organizations at the integrated, optimal, or advanced levels of maturity (Cech et al., 2018). Furthermore, Al Rashdi and Nair (2017) proposed a framework for data maturity consisting of people, process, and platform. With a general focus on culture, team, and process, participants heavily supported the people and process aspects of this design, with some participants touching on the design of platform as well.

By applying identified themes to the second research question, specific actions organizations can take to institute a data-driven culture begin to materialize. This refers to transforming culture across the entire span of the organization and is focused primarily on altering the perception of data-driven technologies and decision support tools at a company-wide level. Participants explained that leaders and change agents must follow a generic set of activities to change a culture, with some activities customizable to fit their desired environment. Participants added that, for a data-driven culture specifically, organizations should carefully build cross-functional business intelligence teams. Furthermore, businesses can catalyze cultural change by implementing a wealth of supportive processes and procedures, most related to data governance. These activities satisfy the question posed and serve to indicate what actions organizations can take to institute a data-driven culture.

Research Question 3. The third research question attempts to explain the ways business analysts can persuade leaders to turn over a degree of decision-making power and allow decision support tools to guide choices in the organization. Unlike the second research question, which sought to understand at a high level how a culture can be transformed, this question investigates how single individual decisions can be influenced by data-driven decision support tools. Participants described two major ways organizations can persuade business decision-makers to adopt a decision supported by data, as well as one way that a company's culture supports data-driven micro-decisions.

Each decision in an organization is made up of a problem and two or more known or unknown choices. Decision-makers must weigh each of these choices using all readily-available information and make a determination as to which choice is best for the organization and its strategy. Decision support tools are intended to provide information that removes doubt or uncertainty from particular choices or groups of choices. Inherent in the use of these tools is the recognition of their value and trust in technological systems. Participants identified persuasive techniques to help improve the perception of technical decision support tools. Participants also noted various qualities of data that can improve trust in recommendations. Finally, several participants discussed the ways culture can contribute to organizational buy-in and, therefore, usage of and reliance on decision support tools.

Participants first made mention of persuasive techniques that can be utilized when trying to convince decision-makers to rely on data-driven technologies. Those interviewed in the study noted that decision-makers frequently resist usage of decision support tools, in part due to a lack of understanding and in part due to a resistance to change. Persuasive techniques discussed throughout the first theme can allow business intelligence professionals and change agents to change perceptions of data-driven technologies and drive adoption among organizational decision-makers. Participants stated that business intelligence team members and change agents can socialize activities and distribute propaganda throughout the organization, providing decision-makers at all levels of the company with an awareness of data-driven initiatives. Also discussed was the need for analysts to prove the usefulness of decision support tools by observing the six aspects of data trustworthiness. Participants explained that those looking to affect change should demonstrate the impact of data-driven technologies to potential users, especially those resisting adoption. Finally, employing technical and business consultants, even in a minor support role, can help provide credibility to data-driven initiatives. By participating in these activities, business intelligence teams can persuade decision-makers to consider the adoption of data-driven technologies.

For leaders and other organizational decision-makers to adopt advanced, data-driven decision support tools must convey a sense of trustworthiness. Participants identified six dimensions of trust in data that contribute to an overall level of comfort on behalf of decision-makers and observers of data. Accuracy and consistency were two major topics of discussion, with 16 (89%) and 11 (61%) participants identifying these dimensions, respectfully. Accuracy of data, participants claimed, refers to the need for data-driven metrics to correctly represent reality. Consistency, according to participants, represents the stability of calculations across time and platforms. Decision support tools should also be highly available. Of the 18 participants, 12, or 67%, noted that data should be available when and where it is needed. Six participants, or 33%, explained that insights should be actionable and be relevant to the job functions of the consumers. Many participants, 12 of 18 (67%), discussed the need for data integrity, or the closeness to which data stored in a database matches the inputs provided by the data originators. Finally, four participants, or 22%, referred to the need for datasets to be complete and robust. In observing these six dimensions, organizations can create insights that are useful and trustworthy in the eyes of decision-makers and data consumers. Trustworthy insights, according to participants, are necessary when encouraging leaders and decision-makers to adopt data-driven technologies.

Persuading individuals to incorporate decision support tools in their daily job role was identified as a difficult task. Eight participants, or 44%, suggested the need for cultural buy-in to grow data maturity. Participants stated that when a decision-maker supports a data-driven environment, that individual will become more enthusiastic about new technologies. The right culture should encourage decision-makers to rely on data when making choices and can still be somewhat controlled at the individual level.

The conceptual framework, informed by several researchers, provides several components for placing context around the topics discussed by participants pertaining to persuasion. The maturity model provided by Cech et al. (2018) explained the need to become data-driven by providing decision-makers with useful and correct information. Cech et al. (2018) also discussed the need for robust, connected datasets, a topic that was of particular interest to participants. Farah (2017) and Skyrius et al. (2016) explained that for decision-makers to use decision support tools, organizations must support data and technology management efforts. According to Boncea et al. (2017) and Chen and Nath (2018), businesses should improve technical maturity to improve adoption of technologies. Researchers generally support or allude to the same ways that participants asserted decision-makers can be persuaded to utilize decision support tools.

When making choices, decision-makers must seek to uncover the most information that can be used as inputs to inform their selection. Decision support tools developed by business intelligence teams are intended to facilitate this process. When decision-makers are provided with these tools, they must be able to trust in the information provided. Participants state that without this trust and without the appropriate persuasive techniques employed, decision-makers instead fall back solely on their own intuition. Participants identified various forms of persuasion, dimensions of trust that must be observed, and aspects of culture that should be managed to improve adoption of data-driven technologies.

Summary of the Findings

The themes and patterns identified during the data collection, coding, and analysis processes serve to inform understanding of the forces driving data-driven decision-making and the specific research questions posed. Participants discussed topics categorized into three major themes and achieved alignment on high-level concepts. Although some debate can be expected regarding fine details, participants largely agreed upon major sources of success or challenges within their own organization. Participants first found that data-driven decision support tools should be trustworthy and reliable to promote a data-driven culture. This also involved the need for business intelligence professionals to engage in persuasive discussions and activities with organizational decision-makers. Additionally, participants discussed the need for cross-functional data-driven teams to be clearly defined and populated with a diverse set of individuals with a wide-range of skills represented. Participants also argued that business intelligence teams should be governed and engaged in highly process-driven work to encourage consistency and agility. Obtaining a deep understanding of these themes and interactions and overlap between them can aid in expanding knowledge related to data-driven decision-making. Understanding these forces and levers provides researchers and practitioners with additional knowledge and resolve the research questions posed in this study.

Applications to Professional Practice

The findings of the study provide natural applications to the field of strategic management. Within the scope of the findings, participants identified a host of discoveries with great implications for potential organizational change. Participants noted the need for defining strategy in terms of team design and instructions. Furthermore, a great number of opportunities for improvement in work processes were identified. These improvements promote data-driven decision-making through improving organizational trust in data-driven technologies. According to participants, increased trust in data leads to improved data maturity. Each of these high-level strategic actions can influence and reinforce a culture of data-driven decision-making.

A strategic business manager is often an individual who is tasked with developing and executing an organization's high-level plans intended to achieve goals set forth by the company. The strategic transformation of decision-making processes may be the responsibility of an organizational leader or businesses may designate an individual or group of employees in other job roles to perform these tasks. Strategic business managers must assemble the proper individuals that can work as a team to define and execute the appropriate strategy to achieve the desired goals. Participants identified several themes that indicate a heavy initial reliance on strategists when migrating toward a data-driven culture.

According to several participants, a culture of data-driven decision-making can be modeled and measured by data maturity. A major surprising component of data maturity, overwhelmingly agreed upon by participants, is the confidence organizational decision-makers have in their data and decision support tools. Participants identified a host of elements related to the trustworthiness of data, notably its accuracy, consistency, availability, and actionability. Interestingly, a useful and natural corollary of this finding is the need for organizations to focus attention on improving decision-maker confidence in decision support tools. Participants identified the need to employ persuasive techniques to encourage the adoption of technologies, including socializing opportunities and involving decision-makers in the implementation of such technologies. Improving organizational trust in information and decision support technologies supports data maturity and, as a consequence, helps usher in the desired culture of data-driven decision-making.

Strategic business managers, particularly those charged with transforming culture or implementing data-driven solutions, should be aware of the techniques for transforming culture as well as the structure of teams and their priorities. Understanding the components of a successful culture transformation can greatly improve an organization's ability to execute its strategy. According to participants, a generic cultural transformation strategy requires a long-term commitment, consistent messaging, and a change coalition of leaders or employees willing to be the drivers of organizational revolution. When working to specifically introduce a data-driven culture, business strategy should include financial support of business intelligence teams designed to create decision support tools intended to improve organizational decision-making. Building a diverse team bound by a common goal helps enable the quick turnaround of data-driven projects and provides the organization with a sense of trust in data-driven technologies. This sense of trust is a key component of introducing a data-driven culture.

Organizational strategists can also institute or encourage leaders to institute processes that support the development and usage of data-driven technologies. These processes govern interactions with data and are intended to strengthen and protect significant aspects of trust in data. From the perspective of a strategic business manager, participants explained that data governance processes and procedures dictating the proper usage of decision-making tools can have a significant impact on the trustworthiness of data and, as a result, cultural buy-in. Specifically, data governance processes refer to the methods by which business intelligence teams complete technical implementations and follow proper development frameworks, as well as the way these teams interact with decision-makers and manage expectations. Each of these processes must be carefully designed to ensure adherence to the principles of trust in data and the principles of a successful culture transformation. According to participants, strategic business managers must focus on building business intelligence teams and defining these concepts.

Participants explained that businesses that follow these recommendations can expect to see improvements in data maturity and, as a result, improvements in the targeted organizational metrics. Progression through data maturity frameworks indicates a healthier relationship between organizational decision-makers and the available data. Furthermore, more mature businesses understand the role of data and decision support tools within their own internal processes and know when to fully rely on such tools and when to treat them as strictly a supplement. These businesses often utilize more advanced algorithms to provide more useful insights and automations within the organization. Utilizing data to support decision-making, enabled by a data-mature culture, allows for improved financial and non-financial measurements. A properly-implemented data-driven culture can lead to gains in revenue, cost savings, and improved service. In these ways, transforming culture into one of data-driven decision-making can be an attractive and lucrative option for businesses.

In relation to the conceptual framework, participant recommendations generally allow organizations to make strides in data maturity. The framework recommended by Cech et al. (2018) focused on improving technical capabilities and culture, including tasks such as building centralized data repositories, creating data dictionaries, improving technical skills, and conducting internal reviews. Bogdan and Lungescu (2018) and Chen and Nath (2018) provided analysis of data maturity models, explaining that they frequently omit the importance of transforming culture through soft-skills and internal marketing. Al Rashdi and Nair (2017) analyzed several models as well, showing that they often present business challenges as a one-time challenge and do not consider ongoing activities that must be completed. Participants included each of these considerations in their examination of data maturity, addressing at length the need for a robust culture transformation and ongoing efforts and processes to protect their investment. Skyrius et al. (2016) argued that the appropriate culture drives maturity as well as agility, acceptance, and adoption. In a somewhat contrasting opinion, participants indicated that a data-driven culture and data maturity are somewhat synonymous.

The findings of the study can and should be implemented in a way that is compatible with biblical understandings of innovation and technology. Tennie et al. (2017) and Vella (2016) explained that technical innovation has been used throughout human history to advance mankind. Keller and Alsdorf (2012) found that creation itself is a form of innovation and was seen by God as good. Giffone (2019) and Kirkpatrick (2019) warned that technology should be used morally and to achieve moral ends. As opposed to humanity's unrighteous use of technology in Genesis 11 to build the Tower of Babel, Giffone (2019) pointed to Nehemiah's use of technology to protect Jerusalem as an example of righteous biblical innovation. Organizations should weigh the use of technology as a decision support tool against moral and ethical frameworks to ensure that the desired use cases are compatible with biblical standards.

The findings of the study indicate a wide-ranging suite of activities organizations can engage to improve data maturity and institute a culture of data-driven decision-making. Participants suggested defining their data philosophy and teams and finding ways to methodically transform culture. Additionally, participants noted that organizations should institute processes that encourage data-driven decision-making and trust in decision support tools. Participants finally showed that this trust in data encourages adoption of data-driven technologies and is the key to building and maintaining the desired culture.

Recommendations for Action

The findings of the study and the applicability to practice inform the recommendation of many specific actions that organizations can take to introduce a culture of data-driven decision-making. These recommendations contain a number of activities that leaders and change agents can engage to improve organizational acceptance and enthusiasm for decision support technologies. Suggestions focus primarily on the transformation of culture, the development of a data-driven business intelligence team, and the definition of data governance processes. Because of the wide scope of culture, most employees in the organization will be directly or indirectly affected in some way by these changes.

1. Organizational leaders and change agents should acknowledge the need for smarter, data-driven decision-making and the enabling decision support tools.
2. Organizational leaders should be willing to invest in the technologies and skills required to introduce decision support tools.
3. Change agents should document the current state of organizational culture, taken as a whole and specifically with regard to decision-making processes.
4. Organizational leaders and change agents should define the desired future state and what the appropriate level of data maturity is for their business.
5. Organizational leaders and change agents should define a change coalition of diverse individuals at all levels of the organization who are tasked with promoting the desired future culture.
6. Change agents should identify and recruit an executive sponsor who will provide support at the highest levels of the organization and remove barriers to change.

7. Organizational leaders and executive sponsors should frequently make public declarations of support for data-driven initiatives through various platforms such as town halls and memos.
8. Change agents should acquire opportunities for training and education and make these resources available to organizational leaders, decision-makers, and business intelligence professionals.
9. Change agents should adopt a continuous improvement mindset and allow this philosophy to permeate throughout all activities and initiatives.
10. Organizational leaders and change agents should define a business intelligence team responsible for the development or acquisition of decision support tools.
11. Organizational leaders and change agents should identify business intelligence team members, selecting members from a diverse group of IT and analyst professionals with wide-ranging skillsets in the fields of data analysis, IT infrastructure, mathematics, statistics, and business.
12. Organizational leaders and change agents should determine whether their business can benefit from the use of external consultants and match potential consultants to their specific needs.
13. Organizational leaders and change agents should build a team-driven environment of collaboration and cooperation.
14. Organizational leaders and change agents should define project selection and prioritization procedures that seek input from a diverse committee of individuals and make determinations of what issues should be targeted for improvement.

15. Business intelligence teams should define the technical requirements and infrastructure that support the known needs of the organization and provide scalability for future needs.
16. Business intelligence teams should define and adopt procedures governing the development of new tools. Procedures should follow an agile methodology and encourage decision-maker participation, system stability, and fast, regular updates.
17. Business intelligence teams should establish protocols for interacting with decision-makers and ensuring organizational confidence in technologies and team members.
18. Change agents and business intelligence teams should define strategies for deploying new technologies and carefully manage the adoption of such tools.
19. Business intelligence teams and change agents should develop processes governing the way decision-makers and operators interact with technological systems.
20. Organizational leaders and change agents should identify the success factors by which data-driven initiatives will be measured.

To a degree, all or most members of the organization will be affected by data-driven initiatives. Because culture spans the entire organization, it would be impractical and inappropriate to attempt modifying practices for only a subset of employees. Although decision support tools may not be provided to all employees initially, the scope of data-driven decision-making demands that data generators be acknowledged. These individuals may act as producers of data, although they may not immediately be consumers of data-driven technologies. Therefore, organizational leaders and change agents must take a holistic approach to becoming data-driven, treating the employee base as a single, homogenous group.

Although all members of the business will be affected, most will be only superficially or tangentially involved in efforts in the beginning. Most affected by this transformation will be high-level organizational leaders, those in IT and analyst positions, and those targeted as early adopters of data-driven technologies. Leaders will be required to provide support for initiatives and make determinations about team population and project selection and prioritization. IT and analyst professionals will be expected to provide tools based on organizational needs that can be used to improve or replace decision-making by eliminating risk and unknowns. Operational, tactical, and even strategic decision-makers will be affected to a degree by the adoption of data-driven technologies in their respective areas. Those who are not targeted as early adopters must still play a participatory role in that their inputs must be sanitized for use in tools that may be adopted by other areas of the business.

It is the responsibility of organizational leaders and change agents to provide initial communication to the affected individuals during a data-driven culture transformation. This can most appropriately be done through targeted meetings and town halls. For the most-affected individuals, such as those selected for inclusion in business intelligence efforts, direct discussions would be most appropriate. For those affected only indirectly or tangentially, town halls and corporate memos may be more acceptable. Throughout project selection and prioritization, if business intelligence teams are not part of discussions, leaders and change agents must assume responsibility for the effective communication of this information to the team. When working with individual decision-makers throughout the development of decision support tools, business intelligence teams should work to communicate pertinent information back and forth between the individuals. Effective communication between all parties is instrumental to creating a successful and trusted environment of data-driven decision-making.

Recommendations for Further Study

Although this qualitative research study covered a large number of topics related to cultures of data-driven decision-making, there exist numerous opportunities for additional research. The case study performed was bounded by the specific context of a medium-sized transportation business and focused on a culture of generic data-driven decision-making. Topics that may require additional examination include a focus on advanced technologies such as artificial intelligence and machine learning, the transferability of findings to other industries or organizations of different sizes, and the experiences of decision-makers at more and less data-mature companies.

Questions and responses that were part of the field study frequently referred generically to data-driven tools. When discussing specifics, participants often responded with the erroneous belief that decision support tools are limited to simple data visualizations. In practice, such tools can range from data visualizations to predictive analytics, artificial intelligence, and machine learning. Additional research narrowed to focus on more advanced technologies may be necessary. It is likely that participant responses would be somewhat different in cases of decision replacement technologies (such as automations) instead of decision support tools.

Furthermore, the study was concentrated on a single medium-sized trucking organization. Although transferability of the findings is ultimately the choice of the reader, it is likely that many of the findings are applicable across the trucking industry and possibly other industries. However, it is unlikely that findings are immediately transferable to small or large-sized organizations. Additional research in smaller transportation businesses and larger organizations may reveal different approaches to data-driven decision-making. Research in other industries may confirm or refute the transferability of findings between industries.

Organizations may hold different opinions regarding data-driven cultures depending on their own data maturity. Businesses who occupy the advanced stage of maturity are likely to know what activities help reach the desired culture, though companies who are more immature may not have well-defined opinions. Studying this aspect of data-driven decision-making, through considering organizations at various phases of data maturity, may help to better understand the progression of becoming data-driven. Even the most mature organizations may not, on their own, provide an accurate view of their past, more immature selves.

These considerations may help provide a deeper look into cultures of data-driven decision-making that can inform future researchers and practitioners. Studying the application of more advanced technologies, organizations of different sizes and industries, and organizations of diverse maturity can help provide additional triangulation that may have wider implications for business taken as a whole. Alternatively, results may indicate that findings are not transferable among organizations of different sizes and industries. In all future studies, research questions should consider a narrowing of the scope to particular technologies, specific types of decision-making, or different aspects of strategic management. This may help future researchers provide the most useful qualitative analysis concerning cultures of data-driven decision-making.

Reflections

This study involved the participation of 18 members of an organization and took the form of a qualitative case study. Participants represented employees, managers, and top executives and included individuals from all areas of the organization involved in the production or consumption of data. Over the weeks the researcher was engaged with participants, several biases and preconceived notions were identified and mitigated. Additionally, many surprising concepts emerged and directed analysis and recommendations provided as part of the study.

During initial interviews with participants, some questions in the interview guide were identified as problematic due to potential unclear wording. In future interviews, language was modified in some questions to make the intent clearer. Additionally, the order of the questions caused some confusion due to shifting topics. In later interviews, questions were tailored slightly differently to account for these shifts. The researcher quickly identified the potential for asking leading questions due to preconceived ideas in the technology arena. During the field study, the researcher was careful to ask neutral questions and approach discussions and coding from a constructivist approach. Similarly, after coding was completed, the researcher was careful to avoid giving undue weight to a particular topic or idea. This was accomplished by balancing ideas based on the number of unique participants who discussed each topic. The departments and job roles of participants was also occasionally considered to ensure a diverse set of ideas would be presented in the study results.

During the interview phase, the researcher noted the propensity of some participants to provide undue weight to the technology aspect of data-driven decision-making. This was in opposition with the study's goal of primarily focusing on culture. Participants likely gravitated toward technical discussions due to the technology background of the researcher. Although discussions of technology were insightful, in these cases the researcher worked to steer conversations toward the experiences of individual participants. This ensured the acquisition of findings related specifically to culture, the focus of the study.

Throughout the coding phase, the researcher noted several interesting findings that contributed to a change in understanding of data-driven cultures and served to inform the direction of the recommendations provided as part of the study. First, the researcher identified the importance of trust in a data-driven culture, and due to the prevalence of this topic in conversations with participants, decided that this was a primary need in a culture transformation. In a second realization, the researcher noted the importance of creating processes, known as data governance, to protect trust in data. A third finding marked a shift in belief of data-driven initiatives being a technology-driven endeavor to being a team-driven effort. The fourth and final discovery demonstrated the need for cultures to be implemented through a change coalition rather than top-down mandates.

Discussions with participants revealed a number of topics with potential moral and ethical implications. For example, data-driven decision-making extends to automation, which can potentially result in less need for individuals in certain job roles. Data collection may also invoke thoughts of invasions of privacy. In all activities involving technology, organizational leaders must remember the dueling applications of technology found in the biblical accounts of the Tower of Babel and the walls of Jerusalem. In one case, the people of the world built a tower for their own glorification. In the other, Nehemiah led the people of Jerusalem in a construction project to defend their own people. When working with technology, organizations must remember these testimonies and ensure that their own intentions are pure.

Summary and Study Conclusions

The problem targeted in this study was the inability of companies to become data-driven, despite their own technical capabilities and resources (Bogdan & Lungescu, 2018; Galbraith, 2014; Grover et al., 2018; Olufemi, 2019). Organizations often struggle with transforming their culture, especially due to occasional resistance from decision-makers and strategic leaders (Bogdan & Lungescu, 2018; Galbraith, 2014). The purpose of the study was to investigate and understand the ways businesses can create a culture of data-driven decision-making that supports improved organizational performance. Garcia-Perez (2018) and Halaweh and El Massry (2015) explained that understanding these processes helps companies transform culture. The study operated under a single driving research question: How can organizations transform their corporate philosophy into a data-driven culture that supports both productivity and accountability? Follow-up questions focused on the construction and introduction of a data-driven culture at a high level, and the way business analysts can persuade leaders to adopt technologies for micro-level decision-making. An in-depth review of the existing literature revealed the state of prior research and helped identify a gap in prior knowledge. Alameen et al. (2016), Chai et al. (2017), Parra-Romero et al. (2017), and Roth (2016) discussed the specific need for trucking organizations to implement decision support solutions. Various other researchers explain that understanding how to create a data-driven culture is essential to data maturity and encouraging adoption of technologies, acknowledging that research frequently ignores this aspect of business (Cech et al., 2018; Farah, 2017; Garcia-Perez, 2018; Halaweh & El Massry, 2015; Olufemi, 2019; Skyrius et al., 2016).

For this study, a qualitative methodology was employed to allow for understanding the essence of the experience of becoming data-driven (Guillen, 2019). Creswell and Creswell (2018) explained that the qualitative methodology encourages studying a concept by working with observers and participants. Adopting a constructivist approach through a case study design helped to understand the causes and interactions between causes that result in a data-driven culture (Wynn & Williams, 2012; Yin, 2018). During the field study, 18 participants were recruited to take part in semi-structured interviews intended to provide insight into the research questions. During and after the interview process, transcripts were coded to help identify themes. After several rounds of coding, themes began to emerge and a logical framework of recommendations was realized.

Participants identified three primary themes that served to generate the eventual study recommendations and conclusions. First, participants noted that the foundation of a data-driven culture is trust in data systems and decision support tools. This is comprised of several dimensions of trust, as well as the tasks analysts must complete to persuade decision-makers to adopt technologies. As a second theme, participants further discussed the need to clearly define cross-functional data-driven teams and to staff these teams with individuals with a diverse set of skills. Finally, participants explained that organizations should institute data governance and standard work processes that help regulate the production and consumption of data within the business. These processes encourage consistency and agility in the creation and deployment of data-driven decision support tools.

The identified themes naturally form a number of applications practitioners can use to inform their own culture transformations. Recommendations to business leaders and change agents encourage these individuals to improve data maturity through defining data philosophy and teams, as well as identifying activities that can help improve culture. Participant responses indicated that adoption of decision support tools is contingent on trust in data, which can be facilitated through the institution of data governance processes. As a result of these applications, specific recommendations for action in business include taking concrete steps to transform culture, develop a data-driven cross-functional team, and building data governance processes. In an academic environment, future researchers are encouraged to place greater emphasis on advanced technologies in studies, conduct research at organizations of smaller or larger sizes, and work to understand the experiences of lesser and more mature data-driven companies.

Gaps in prior research related to the lack of understanding of data-driven cultures, especially within transportation organizations (Alameen et al., 2016; Chai et al., 2017; Parra-

Romero et al., 2017; Roth, 2016). Additionally, researchers noted the difficulty associated with the act of transforming culture (Cech et al., 2018; Farah, 2017; Garcia-Perez, 2018; Halaweh & El Massry, 2015; Olufemi, 2019; Skyrius et al., 2016). Participants provided a comprehensive framework of a culture of data-driven decision-making that helps understand both its qualities and the ways organizations can encourage its adoption. This framework serves to satisfy the gaps in the literature. By observing the resulting recommendations, medium-sized organizations can design and implement a culture of data-driven decision-making and improve their own performance and productivity.

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Appendix A: Permission to Reprint Figure 1

Transcribed from Cech et al. (2018).

Appendix B: Permission Letter

February 19, 2020

Kevin Rogers
Doctoral Candidate
Liberty University School of Business
1971 University Blvd.
Lynchburg, VA 24515

Dear Mr. Rogers:

After careful review of your research proposal entitled "Creating a Culture of Data-Driven Decision-Making", I have decided to grant you permission to conduct your study at USA Truck and contact our faculty/staff and invite them to participant in your study.

Check the following boxes, as applicable:

☐ I/We are requesting a copy of the results upon study completion and/or publication.

Sincerely,

[redacted]

Kim Littlejohn
Vice President, Chief Technology Officer
USA Truck

Appendix C: Recruitment Letter

Dear Recipient:

As a graduate student in the School of Business at Liberty University, I am conducting research as part of the requirements for a Doctor of Business Administration degree. The purpose of my research is to better understand the ways in which organizations can grow data maturity through transforming culture, and I am writing to invite eligible participants to join my study.

Participants must represent an eligible organization and work with organizational data, as a producer or consumer, in an official capacity. To be eligible, organizations must operate in the transportation industry in the southern United States, maintain 500 to 2500 active units, employ between 100 and 500 office staff, employ at least 75% of information technology team members in-house, and have adopted or be in the process of adopting data-driven technologies. Participants, if willing, will be asked to complete a recorded 60 to 90-minute interview and take part in a 5 to 10-minute follow-up session to verify characterizations of their beliefs. Names and other identifying information will be requested as part of this study, but the information will remain confidential.

In order to participate, please contact me at [redacted] or [redacted]@liberty.edu to schedule an interview.

A consent document will be given to you at the time of the interview. The consent document contains information about my research. Please sign the consent document and return it to me at the time of the interview.

Sincerely,

Kevin Rogers
Doctoral Candidate
Liberty University School of Business
[redacted]@liberty.edu

Appendix D: Consent Document

Consent

Title of the Project: Creating a Culture of Data-Driven Decision-Making
Principal Investigator: Kevin Rogers, Doctoral Candidate, Liberty University School of Business

Invitation to be Part of a Research Study

You are invited to participate in a research study. In order to participate, you must be employed full-time in a position that produces or consumes data in an official capacity at an eligible organization. Eligible organizations must operate in the transportation industry in the southern United States, maintain 500 to 2500 active units, employ between 100 and 500 office staff, employ at least 75% of information technology team members in-house, and have adopted or be in the process of adopting data-driven technologies. Taking part in this research project is voluntary.

Please take time to read this entire form and ask questions before deciding whether to take part in this research project.

What is the study about and why is it being done?

The purpose of the study is to better understand the ways organizations can grow data maturity through transforming culture. The study is intended to explore the processes by which an organization can create a culture of accountability and productivity. The research will work to understand how a business can replace human decision processes with more reliable and informed data-based algorithms.

What will happen if you take part in this study?

If you agree to be in this study, I would ask you to do the following things:

1. Take part in a 60 to 90-minute interview discussing the theories behind data-driven decision-making and culture transformation. This interview will be recorded and transcribed.
2. Take part in a 5 to 10-minute review session to verify the validity of the researcher’s analysis of your contributions.

How could you or others benefit from this study?

Participants should not expect to receive a direct benefit from taking part in this study.

Benefits to society include a deeper understanding of cultures of data-driven decision-making. The study will be part of a larger body of work describing how strategic business management relates to implementing such a culture. Organizations that successfully implement a supportive culture should see improvements in performance.

What risks might you experience from being in this study?

The risks involved in this study are minimal, which means they are equal to the risks you would encounter in everyday life.

How will personal information be protected?

The records of this study will be kept private. Published reports will not include any information that will make it possible to identify a subject. Research records will be stored securely, and only the researchers will have access to the records.

- Participant responses will be kept confidential through the use of codes. Interviews will be conducted in a location where others will not easily overhear the conversation.
- Data will be stored on a password-locked computer and may be used in future presentations. After three years, all electronic records will be deleted.
- Interviews will be recorded and transcribed. Recordings will be stored on a password-locked computer for three years and then erased. Only the researcher will have access to these recordings.

How will you be compensated for being part of the study?

Participants will not be compensated for participating in this study.

Is study participation voluntary?

Participation in this study is voluntary. Your decision whether to participate will not affect your current or future relations with Liberty University. If you decide to participate, you are free to not answer any question or withdraw at any time without affecting those relationships.

What should you do if you decide to withdraw from the study?

If you choose to withdraw from the study, please contact the researcher at the email address/phone number included in the next paragraph. Should you choose to withdraw, data collected from you will be destroyed immediately and will not be included in this study.

Whom do you contact if you have questions or concerns about the study?

The researcher conducting this study is Kevin Rogers. You may ask any questions you have now. If you have questions later, **you are encouraged** to contact him at [redacted] and/or [redacted]@liberty.edu. You may also contact the researcher's faculty sponsor, Dr. Melissa Connell, at [redacted]@liberty.edu.

Whom do you contact if you have questions about your rights as a research participant?

If you have any questions or concerns regarding this study and would like to talk to someone other than the researcher, **you are encouraged** to contact the Institutional Review Board, 1971 University Blvd., Green Hall Ste. 2845, Lynchburg, VA 24515 or email at irb@liberty.edu.

Your Consent

By signing this document, you are agreeing to be in this study. Make sure you understand what the study is about before you sign. You will be given a copy of this document for your records. The researcher will keep a copy with the study records. If you have any questions about the study after you sign this document, you can contact the study team using the information provided above.

I have read and understood the above information. I have asked questions and have received answers. I consent to participate in the study.

☐ The researcher has my permission to audio-record me as part of my participation in this study.

______________________________	______________________________
Printed Subject Name	Signature & Date

Appendix E: Permission to Reprint Figure 2

Dear Kevin Rogers,

Thank you for your request via Copyright.com ticket 600008041 to use Fig. 2.4 from "Case Study Research and Applications" within your forthcoming thesis/dissertation. I am pleased to report we can grant your request without a fee.

Please accept this email as permission for your request. Permission is granted for the life of the edition on a non-exclusive basis, in the English language, throughout the world in all formats provided full citation is made to the original SAGE publication. Permission does not include any third-party material found within the work.

As permissions have been granted via this email, we will cancel your Copyright.com order. If you have any questions, or if we may be of further assistance, please let us know.

Kind regards,

Mary Ann Price
Rights Coordinator
SAGE Publishing
[redacted]
Washington, DC 20037
USA

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www.sagepublishing.com

Appendix F: Interview Guide

Introductory Statement

The central research question that will guide the investigation related to this study is: How can organizations transform their corporate philosophy into a data-driven culture that supports both productivity and accountability? Research questions will include: (a) what constitutes a data-driven culture, (b) what actions can organizations take to introduce a data-driven culture, and (c) how can business strategists persuade leaders to turn over a degree of decision-making power?

The following interview questions provided will give the researcher a specific set of items that must be investigated to best understand data-driven culture transformation. Such questions aim to explain the specific ways organizations can increase their data maturity. These questions also ensure that the researcher addresses individual actions—as well as overarching campaigns—organizations put in place to drive better decision-making.

Interview Questions

1. What constitutes a data-driven culture?
2. How does a data-driven culture contribute to an organization’s ability to collect, report, and use information in smarter, meaningful ways (“data maturity”)?
3. What are the key components of a generic culture transformation?
4. What actions can organizations take to introduce a data-driven culture?
5. What strategic internal and external partners are necessary to create a data-driven environment?
6. How can business strategists persuade leaders to turn over some degree of decision-making power to drive decisions based on data and smarter algorithms?

7. How can organizations uncover and prioritize specific use cases for their data?
8. Who should be responsible for uncovering and prioritizing use cases?
9. What types of activities can provide organizational researchers and data scientists with the tools and backing they need to be most effective?
10. What types of problems should data scientists work to solve early in the process to gain organizational trust?
11. What positions are necessary to support a data-driven endeavor? Should such positions be filled by full-time employees or people working on a cross-functional team?
12. What skills and qualities are necessary for team members directly working to support a data-driven transformation?
13. What ongoing practices are necessary to maintain a data-driven culture after implementation?
14. What are the success factors defining a culture transformation?
15. What are the risks associated with a data-driven culture transformation?
16. What are the risks associated with avoiding a data-driven culture transformation?
17. How can organizations measure the progress of their own data transformation?

Closing Statement

The questions asked are intended to address the problem of adopting a data-driven culture, as well as to satisfy the purpose of this study. The questions aim to directly answer the two primary issues identified in the surveyed literature. Specifically, the research questions address how to transform a culture into a data-driven environment, as well as how to transfer decision-making power to data models. The interview questions provided give more specific areas of interest that point the research in a particular direction while supporting the overall goals of the study.

Appendix G: List of Primary Codes

accountability
actionability of data
adherence to process
adoption of technologies
agile development
analyst-driven solutions
assimilation to culture
availability of data
business consultant involvement
buy-in for culture
celebrate wins
centralized data repositories
change management
collection of data
committee-driven goal setting
common goal
common responsibility for culture
common responsibility for goals
competitor analysis
consistency of data
consistent messaging
continuous improvement
criticality of data
culture affects retention
culture affects revenue
culture as motivation
culture spans organization
data as decision-making supplement
data as metric
data dictionary
data integrity
data proves itself
decision-making process
define current state
defining culture
deliverable-based progress
demonstrate improvement
demonstrate individual impact
effect of automation
effect of turnover
effect on morale
embeddedness of data
empower analysts
exception management

executive sponsor
familiarity with data
gap-driven data analysis
goal-driven data analysis
hands-off supervision
IT consultant involvement
IT-driven solutions
impact-driven data analysis
incentives
individual-based goal setting
interpretation of data
invest in analysts
invest in technology
limitations of data
limitations of resources
methodical transformation of culture
momentum
moral and ethical quandaries
people element of business
performance as result of maturity
presentation of data
process review
project champion
propaganda
purpose of data
quantifiability of business
requirements gathering
resistance to change
resource-based strategy
robustness of data
routine reviews of data
routine reviews of goals
sample size
seasonality of data
servant leadership
service culture
skill: IT infrastructure
skill: basic data analysis
skill: creative problem-solving
skill: documentation
skill: innovativeness
skill: inquisitiveness
skill: interpersonal EQ
skill: leadership
skill: mathematics
skill: open-mindedness

skill: process management
skill: project management
skill: stake in data
skill: understand application
socialize projects
speed to market
staying the course
team member confidence
team member diversity
team-driven solutions
third-party software
too much data
top-down culture transformation
top-down goal setting
training and education
trust in data
trust in environment
understanding own contributions
user involvement
value-driven culture transformation
workspace design