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Exploring Best Practices to Utilize Business Intelligence Systems

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This is to certify that the doctoral study by

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has been found to be complete and satisfactory in all respects,
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Abstract

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MA, Liberty University, 2011

BS, Liberty University, 2009

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

Organizational leaders who can manage business intelligence system (BIS) resources may achieve sustainable success in economic, political, and corporate environments. The review of professional literature indicated that effective resource management in a BIS environment requires the establishment of best practice. The purpose of this qualitative, single-case study was to explore best practices among 9 BIS practitioners for effective resource management. Participation criteria included the active engagement in BIS professional disciplines and the willingness to share their perspectives. The conceptual framework for this study was the cognitive experiential self-theory (CEST). Five leaders and 4 data analysts at an eastern U.S. county government agency were interviewed. Using computer based qualitative data analysis software to assist with the coding process, interview transcripts and the published directives of government agency leaders were reviewed to identify themes and achieve triangulation. Five themes emerged: the need for comprehensive policies and procedures for creating operating standards, updated data acquisition training, human capital dynamics management for improved efficiency, protocols for transforming raw information into knowledge, and safeguards for preventing bias in data analysis. Findings derived from this study could contribute to global social change as BIS leaders use best practices to improve resource and data management proficiencies for rapidly transforming information into knowledge for developing policies, services, and regulations that affect public safety, fiscal planning, and social risk management.

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Dedication

I dedicate this paper to my father and mother, James and Norma McHenry, thank you for your unconditional support and encouragement. Without you, Stephanie and I could not have pursued our goals and earned our doctorates. Dad, one of my greatest regrets will always be that I did not graduate before your passing on September 4, 2015, so we could share the experience together. To my sons, Ryan, Zachary, Isaac, and Jacob, I am so proud of you all. You were all great children and now that you are men, you are my best friends. To my sister Sandie and brother Robert Dickerson, thank you for cheering me on to the finish line and understanding my eccentricities. To my sisters, Hope and Faith, you have wonderful families. If there were a doctorate for motherhood, you would both be recipients. To our family friends, Sundi and Brian McLaughlin, without regard for personal gain your family has taken up a post on the wall to guard our freedom. I sincerely thank you for the sacrifices you make to keep us safe; they have not gone unnoticed or unappreciated. If I could choose another brother and sister, I would choose you two. With all of my heart I want to thank the most important person in my life, my wife Stephanie McHenry; DNP. You are one of the most remarkable people I have ever known. You raised four incredible sons, balanced a professional career, earned your doctorate, and spent countless days and nights supporting me without a complaint. I am your son, father, brother, husband, and friend, but I am nothing without all of you. Thank you all.

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I would like to acknowledge my second committee person, Dr. Carol-Ann Faint, and the URR, Dr. Steven Munkeby, for their wisdom and efforts to make the study better. Often the smallest change in a study makes the difference. Thank you for your attention to detail. Also, thank you Dr. Freda Turner for every attempt to make the program better.

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Section 1: Foundation of the Study

The concept of BISs applies to any intelligence tool used to monitor information from different sources to help make managerial decisions in organizations (Affeldt & da Silva, 2013). BIS leaders utilize information technology (IT) for data acquisition and analysis to improve decision-making and productivity (Popovic, Hackney, Coelho, & Jaklic, 2012). The BIS construct provides private business and government agency leaders with the ability to exploit operational data and improve management control systems (Elbashir, Collier, Sutton, Davern, & Leech, 2013). However, BIS implementation is complex, requiring considerable resources with limited error tolerance to maximize critical success factors (Olszak & Ziemba, 2012). Implementing an organizational system for effective BIS operation may require years to complete. Santos (2013) conducted a case study of new organizational safety policies and procedures at a government agency during BIS implementation. The implementation required 7 years to complete due to the complexity of the three-phase process: (a) initial constitution of a planned framework, (b) institutionalizing program practices and procedures, and then (c) finalizing an organizational goal specific strategy through normalization (Santos, 2013). The complexity of introducing policy and procedural changes in an organization make best practices essential to controlling the timeframe of an implementation process.

The failure of BISs can occur for various reasons. Popovic et al. (2012) stated that leadership is the most significant factor influencing the success of IT-intensive strategies, inclusive of BIS. Intelligence systems (IS) leaders may not have the knowledge needed to select the appropriate data analytic techniques in order to achieve precise outcomes (Chen, Roger, & Storey, 2012). The sustainability of BISs may decline if data managers inaccurately assess the level of skill required by personnel to transform data into intelligence (Evans & Kebbell, 2012). Furthermore, with frequency, organizational leaders neglect to identify the existence of *Big Data* and the value of information refined for intelligence-led actions (Evans & Kebbell, 2012). Chen, Mao and Liu (2014) argued datasets incapable of transformation into information with a distinguishable value using conventional means within an acceptable timeframe define the abstract concept referred to as Big Data. Moreover, when BISs are flawed, organizations cannot produce reliable information for a decision support system or do so inefficiently (Olszak & Ziemba, 2012). Among the challenges encountered by organizational leader's employing big data, include the need to maximize BIS performance.

Background of the Problem

In response to industry and vendor interest, BIS researchers focused on IT innovations; however, essential human resource (HR) management factors were ignored (Elbashir et al., 2013). Furthermore, Elbashir et al. (2013) posited that a substantial investment globally by private and government organizations to unlock the potential value of big data for BISs, illustrates the intrinsic value of intelligence-led practices. BISs are useful as constructs for leaders to form management control systems necessary to support regulatory compliance and to govern risk management (Elbashir et al., 2013). The success of economic, political, and organizational systems relies on effective leadership to implement BISs (Parris & Peachey, 2012). Further research identifying the value of effective leadership guidance in business systems is necessary to assess the influences on economic, political, and organizational system operations (Parris & Peachey, 2012).

Government entities in the United Kingdom applied business management philosophies and practices to fulfill government IS responsibilities prior to 1990 (James, 2014). An evolution in the business-to-governmental (B2G) use of BIS models occurred as government officials attempted to meet public needs and services (Bharosa et al., 2013). The use of emerging BIS models by administrators of private organizations allowed leaders of government agencies to address safety and security risks to society, and helped assure financial and social stability (Bharosa et al., 2013). Mirroring IS-led policies in the United Kingdom, government agency leaders in the United States have adopted similar B2G practices (Carter & Phillips, 2013). A paradigm shift in the use of BISs by government agencies necessitated the establishment of innovative information system policies capable of predictive analytics (Gravelle & Rogers, 2012).

Problem Statement

The shortage of 1.5 million knowledgeable business intelligence leaders in the United States may leave corporations with the inability to transform raw data for strategic use (Chen et al., 2012). Sixty percent of successful outcomes generated using a business intelligence system have a direct correlation to leadership (Elbashir et al., 2013). A lack of leadership expertise regarding information management and analysis results in the failure of intelligence systems (Farrokhi & Laszlo, 2013). The general business problem was the selection of an inappropriate cognitive strategy by business intelligence leadership creates data management and analysis inefficiencies. The specific business problem was data management leaders lack best practices needed to utilize business intelligence systems for effective resource management.

Purpose Statement

The purpose of this qualitative, single-case study was to explore the best practices needed by data management leaders to utilize BISs for effective resource management. The population consisted of county government leaders and data analysts in the eastern United States who were using intelligence system methodologies (ISM) within an implemented BIS. According to Ganzert, Martinelli, and Delai (2012), due to recursive processes in an ISM environment, a systematic approach to decision-making involves each person contributing to IS functions. The results of this study may contribute to social change through the utilization of a government BIS framework to improve the development of public safety policies.

Nature of the Study

I selected a qualitative method for this study. Qualitative researchers use interviews, combined with stories, observations, and other pertinent information to acquire research data (Sandelowski & Leeman, 2012). Policy and practice decision-makers use the qualitative research method to gain needed insight into complex business strategies (Sallee & Flood, 2012). In contrast, quantitative researchers implement a variety of methods to gain knowledge about a population (Schrodt, 2014), which result in generalized numeric outcomes (Houghton, Casey, Shaw, & Murphy, 2013). A quantitative research method was not appropriate for this study because I did not obtain statistical data or test a hypothesis. Using the mixed method approach, researchers combine qualitative and quantitative methods to understand a particular problem (Cameron & Molina-Azorin, 2014). Since I gathered information from various sources to gain a multifaceted view of the problem, absent of statistical data, the mixed method approach was not appropriate for this study.

The five strategies for qualitative research are case studies, ethnography, narrative, grounded theory, and phenomenology (Petty, Thomson, & Stew, 2012). I used a single case study design. A case study design allows researchers to explore a multifaceted social phenomenon (Yin, 2014), and permits the researcher to explore numerous data sources, ensuring a multifaceted view of the phenomenon (Hoon, 2013). Therefore, I selected a single case study design to provide a comprehensive exploration of multiple perspectives involving a complex business situation.

The ethnographic researcher explores the beliefs, language, and behaviors of a group by immersing in the culture (Jansson & Nikolaidou, 2013). Since I focused on the participant’s experiences as opposed to cultural immersion, the ethnographic approach was not suitable for this study. Researchers use the narrative design to explore the human experience and collect insight in the construction of personal identities by gathering multiple narratives (Pettigrew, 2013). Insights into the construction of personal identities were not the focus of my intended research, making the narrative design an inappropriate selection. The grounded theory researcher uses collected data to posit a substantive theory about the study population's experiences (Wyatt, 2013). Since I did not seek to develop a theory, grounded theory was not appropriate for this study. Phenomenology allows a researcher to explore the lived experience of a participant group (Moustakas, 1994). Since I focused on causation, as opposed to lived personal experiences associated with a phenomenon, the phenomenological approach was not appropriate for this study.

Research Question

The central research question that will drive this study is: What best practices are needed by data management leaders to utilize business intelligence systems for effective resource management?

Interview Questions

The participants will respond to the following questions during the interview process:

1. What task analyses are necessary to utilize an intelligence system for effective resource management?
2. What skills and training do leaders need to utilize an intelligence system for resource management?
3. What principles can leaders espouse when utilizing an intelligence system to establish best practices to manage resources?

4. What are best practices that may assist leaders in effectively utilizing intelligence systems at government agencies?
5. What data analytic model(s) does your agency need to utilize an intelligence system to identify patterns or themes in information?
6. How do the data analytic model(s) used by your agency transform information into actionable intelligence?
7. What data analytic reasoning process(es) should leaders choose for the implementation of an intelligence system for the proficient use of resources?
8. What information technology requirements are essential for the successful implementation of an intelligence system?
9. What knowledge relating to data analysis technologies and methodologies do leaders need for the effective utilization of an intelligence system to proficiently employ resources?
10. What additional information can you add that would be valuable to this study?

Conceptual Framework

The conceptual framework for this study was the CEST. In 1991, Epstein (2014) published CEST to explain the thoughts, perceptions, and analytic methods of individuals. Epstein stated that essential decision-making factors identified in the CEST model included (a) emotion, (b) cognitive bias, and (c) personal experience. Epstein offered insights into the problem solving and information analysis methods used by BIS practitioners based on the principles of CEST.

Analytic intelligence personnel frequently exhibit specific factors attributed to cognitive and experiential reasoning (Brewster et al., 2014). The decision-making key factors may extend to an individual's information analysis discernment (Cerni, Curtis, & Colmar, 2012). Using the CEST theory, analysts can make sense of multifaceted and convoluted information using positive affect behaviors and intuition (Burton, Heintzelman, & King, 2013). The analytical method must match the propensities of an individual to optimize the positive effects on the decision-making process (Armstrong et al., 2012). Leadership relies on CEST components to advance the analysis of information and resolve problems in dynamic situations (Akinci & Sadler-Smith, 2013).

Organizational leaders use the principles of CEST to reduce the risk of bias decision-making, and improve information processing by allowing analysts to employ experiential and rational reasoning (Neuert & Hoeckel, 2013). Government agency analysts have developed a pronounced experiential thinking style to make decisions expeditiously (Worrall, 2013). According to Skaržauskienė and Jonušauskas (2013), fluid business environments require concise business decisions; the ability to produce accurate business decisions quickly defines an effective business leader (). Effective decision-making requires a system perspective to address the significance of problem convolution. Departure from a system perspective can yield inaccurate decision-making ().

The CEST framework allows organizations to benefit from the advantages of intuitive decision-making without the risk of biased results (Neuert & Hoeckel, 2013). Fostering an environment of experiential and rational analytic integration might improve efficiency (Armstrong, Cools, & Sadler-Smith, 2012). Armstrong et al. (2012) stated that, to optimize the positive effects of the decision-making process, the correct analytical method must match an individual’s analytic propensity.

Definition of Terms

Big Data: Big Data is an abstract concept encompassing datasets incapable of identification, acquisition, management, and processing by conventional information technology and software/hardware tools within an acceptable timeframe (Chen, Mao, & Liu, 2014).

Case-based reasoning: Case-based reasoning is a process used by individuals and artificial ISs to solve new problems, based on comparative situations and resolutions (Shokouhi, Skalle, & Aamodt, 2014).

Cognitive bias processing: Cognitive bias processing is a method of information processing and decision-making involving the conversion of objective evidence and subjective estimates using distorted information (Hilbert, 2012).

Experiential information processing: Experiential information processing is an intuitive cognitive style derived from personal experience used by an individual to organize, represent, and process information based on life experiences (Akinci & Sadler-Smith, 2013).

Field interview: Field interviews typically occur in an unstructured environment requiring an interviewer to listen actively as an interviewee offers answers to questions or information freely without unnecessary interruption (Colomb et al., 2013).

Intelligence cycle (IC): An intelligence cycle is a method of transforming information into knowledge for use by decision-makers, using distinct stages including planning, collection, processing, analysis, and dissemination (Anton, 2013).

Intelligence system (IS): An intelligence system is a formal or informal system used to combine data gathered from different sources into information of value (Rudas, Pap, & Fodor, 2013).

Multivariate reasoning methods: Multivariate reasoning methods are a means of integrating multiple decision-making methods to process large volumes of complex data (Furao, Sudo, & Hasegawa, 2010).

Rational information processing: Rational information processing is an analytical style using mathematic analysis requiring inquiry and evidencing to organize, represent and process information (Akinci & Sadler-Smith, 2013).

Rules-based reasoning: Rules based reasoning is the use of a data-mining algorithm to discover hidden patterns and relations in complex datasets (Kahn & Mohamudally, 2012).

Assumptions, Limitations, and Delimitations

Assumptions are espoused ideas based on information accepted as plausibly true based on a researcher’s representation of the study population, statistical validation, research design, or other explanations of facts (Martin & Parmar, 2012). Limitations are research restrictions commonly beyond the researcher's control that may affect the study design and results (Kirkwood & Price, 2013). Delimitations define the boundaries set by a researcher to prevent the expansion of a study, and to safeguard the feasibility of the research (Becker, 2013).

Assumptions

This research was subject to five assumptions: (a) Leaderships' best practices influence IC success (Popovic et al., 2012). (b) CEST was an appropriate and useful method to understand the data analyst methodologies (Akinci & Sadler-Smith, 2013). (c) BIS leadership lacked best practices to manage resources and meet stakeholder expectations. (d) Interviewing IS leaders, analysts, and information gatherers was sufficient to answer the research question. (e) The participants responded truthfully to the interview questions.

Limitations

Limitations are potential weaknesses of a study (Kirkwood & Price, 2013). Two limitations were present in the study. The first limitation was my research study was restricted to a single county government agency located in the United States and may not reflect the findings of other organizations and geographical locations. The second limitation was that I only utilized a qualitative single-case study to address the research question.

Delimitations

Delimitations are the bounds of the study (Becker, 2013). Two delimiters were present in the study. The first delimitations of this study was that I only interviewed IS leaders and analyst in a targeted county government agency. The second delimitation was that CEST was the sole conceptual framework through which I analyzed the study findings.

Significance of the Study

Contribution to Business Practice

The data collected for the study may contribute to the gap in business practice regarding leaders' administration of BISs in the government and private sectors. Organizations should recognize the need to optimize training and development programs involving the assessment of individual cognitive styles for employees and leaders tasked with IS functions (Akinci & Sadler-Smith, 2013). Understanding and utilizing the benefits of experiential and rational analytics can aid in the development of reliable predictive ISs formed of interdisciplinary skills providing a construct for the efficient processing of Big Data (Chen et al., 2012). The converging dynamics of government and private sector BISs are necessary to construct an effective intelligence infrastructure (Copeland et al., 2012). Innovative private sector business models and management philosophies, inclusive of business intelligence (BI), are alternatives to outmoded government practices (Anton, 2013). Leadership tasked with administering BISs may benefit from best practices to identify data analytic processes and manage outcome expectations related to organizational strategic plans.

Implications for Social Change

The BIS label refers to a systematic chain of tasks, applicable to government or private sector intelligence models (Carter & Phillips, 2013). Leaders of government agencies recognize the value of knowledge-led initiatives via BISs to improve public safety policies (Carter & Phillips, 2013) and are adapting business practices to deliver public safety services (Coyne & Bell, 2011). Carter and Phillips (2013) further stated the practice of extracting intelligence from data for decision-making has evolved since the 1970's. Moreover, the expanded operation of BISs in the United Kingdom aided government leaders in the design and implementation of the National Intelligence Model and the establishment of a comparable U.S. model, the American Nation Criminal Intelligence Sharing Plan (Gibbs et al., 2015). Using an IS, government agencies in the United States may reduce strategic uncertainty for decision-makers by preparing public service strategies and future capabilities through an anticipatory needs approach (Gibbs et al., 2015).

Darroch and Mazerolle (2013) argued the application of BIS functions by leaders of government agencies may help exploit information previously considered incomplete or too complex for use in the decision-making processes. Further, leaders may gain the knowledge necessary to reduce public anxiety through policy and regulatory development. Government agency leaders use the structure of BISs to develop actionable knowledge and share information related to public safety in a proactive effort to mitigate risks (Carter & Phillips, 2013). The use of intelligence-led initiatives has increased globally the operational effectiveness of government agencies that manage public safety risks to society (Darroch & Mazerolle, 2013). Establishing the leadership best practices that are required to implement BISs may enhance the efficiency of all ISs, whether oriented toward the private or public sector.

A Review of the Professional and Academic Literature

The review of professional and academic literature included peer-reviewed articles and scholarly material relating to BI systems, data analytics and processing models, and CEST to explore leadership best practices needed to implement BISs for effective resource management. I conducted the literature review to establish a scholarly, theoretical foundation to address the research question: What best practices are needed to implement BISs for effective resource management. The following databases were used to identify relevant journal articles and dissertations: ABI/Inform Complete, Business Source Complete, Emerald Management Journals, Sage, Science Direct, and WorldCat resulted in the material for this review (see Table 1). Keywords included *Big Data, best practices, business analytics, business intelligence, business intelligence leadership, data analytics, case-based reasoning (CBR), CEST, cognitive bias and heuristic, IC, intelligence systems,* and *multivariate reasoning.* I gathered information from 123 sources, of which 120 (97.6%) were peer-reviewed journal articles and 118 (98.3%) were published between 2012 and 2016. I also reviewed one seminal book (.008%).

Six categories were in the literature review: CEST, leadership, intelligence cycle, advancements in intelligence systems, value of data within the intelligence systems, and data analytics. Subcategories of the CEST section included advantages of CEST, disadvantages of CEST, and an evaluation of leadership's best practices using CEST.

Subsections of the leadership section include best practices, human resource management and knowledge management. Incorporated into the IC section are subcategories relating to business and government uses for the IC, and challenges and vulnerabilities of the IC. Subsections of the data analytics category encompass CBR, RBR and multivariate problem solving reasoning for BISs.

Cognitive-Experiential Self-Theory

Epstein (2014) formed the cognitive experiential self-theory to explain a person's capacity to integrate preconscious, unconscious, and conscious faculties to process information. As posited by Epstein, and supported by Armstrong et al (2012), CEST includes an explanation of psychodynamic and psychoanalytic concepts (). Data analysts use CEST to analyze large and complex data sets (Worrall, 2013). The functionality of an individual's experiential competence increases through associative learning based on previous experiences (Armstrong et al., 2012). Epstein described the experiential system as rapid, evolutionary, automatic, non-verbal and typically operates outside the scope of awareness; intuitive processing (Epstein, 2014). In contrast, during the decision-making process a person uses rational system functions predominantly within the scope of consciousness, involving the brains slower, deliberate and language based functions; cognitive processes (Epstein, 2014). The heuristics in complex processes associated with perception, learning, and solving problems contribute to leadership decision-making in business (Armstrong et al., 2012).

Armstrong et al. (2012) argued that the cognitive style of business leader shares an association with experiential knowledge. Analysts make decisions based on cognitive experiential systems using two parallel, but different, information-processing methods: experiential and rational reasoning (Neuert & Hoeckel, 2013). The experiential and rational domains of CEST are independent, yet interactive, with one cognitive domain often more pronounced than the other (Curtis & Lee, 2013; Neuert & Hoeckel, 2013). Cerni et al. (2010) stated organization administrators employing increased rational and experiential thinking encouraged the development of transformational leadership techniques. According to Hample and Richards (2014), CEST as an experiential system is part of associative learning, and verbal reasoning has an association with the rational system. Each system operates with different rules and attributes (Hample & Richards, 2014). The experiential domain gleans and stores vital information gained through experiences (Neuert & Hoeckel, 2013). The experiential system functions are automatic (pre-conscious), nonverbal and require little cognitive effort (Hample & Richards, 2014). The rational (conscious) system operates on quantitative concrete data, is relatively slow, and exceedingly cognitive taxing all aspects of the analyst (Worrall, 2013). The components of CEST equate to the quantitative processes in RBR, and the qualitative processes in CBR, to function as support for decision-making (Hample & Richards, 2014). The advantages and disadvantages of CEST relate to the appropriately matching of system processes with the required task (Epstein, 2014).

Advantages of cognitive experiential self theory. The advantages of CEST may account for the theory's rise to distinction in the business intelligence community (Akinci & Sadler-Smith, 2013). A correlation exists between an individual's Rational Experiential Inventory (REI) and the measurable choice to utilize rational or experiential analysis for problem solving (Akinci & Sadler-Smith, 2013). The ability to apply REI as a dual-processing instrument increases the value of CEST in an occupational surrounding (Akinci & Sadler-Smith, 2013). The adaptive nature of experiential (intuitive) and rational (analytical) processing strengthens CEST by exploiting the strengths of both techniques (Hample & Richards, 2014). The CEST method neutralized the complexities of emotion and cognition infused in the analytical processes (Curtis & Lee, 2013).

Scientifically defining CEST served to demystify the inclusion of intuition as a component of the experiential method aiding the analytic system (Curtis & Lee, 2013). Burton et al. (2010) discovered intuitive processing is superior to effortful analysis tasks involving participants evaluating the existence of common three-word associations. Decidedly, intuitive individuals with positive perspectives identify triads (three associated items) with an accuracy and coherence not explained by speed of processing.

Through CEST, the successes of an analyst promotes positive emotion (pride, confidence), increasing the probability of future accomplishment (Carroll, Agler, & Newhart, 2015). The cycle continues as the analyst's self-worth increases and expands the potential for resolving analytical problems. Carroll et al. (2015) cautioned that the positive transformation process often begins with an analyst's personal failures. The feeling of failure then transitions into a protective measure to avoid subsequent deficiency and prevents overconfidence; an event referred to as remedial attribution (Carroll et al., 2015).

Disadvantages of cognitive experiential self theory. The protective controls encouraging the accomplishments of an analyst after a failure could lead to diminished of self-worth and a situational handicap (Carroll et al., 2015). Continued failures cause the analyst to question her or his personal judgment and avoid conclusions (Carroll et al., 2015). With regard to the cognitive processes in CEST, Burton et al. (2010) expressed concerns about the dismissal of individual personalities and the subsequent influence on personal judgment. The personal information processing style of the analyst could compromise the application of intuitive reasoning (Burton et al., 2010).

The REI used to measure CEST, focuses on the subject's perceived ability to use rational or experiential thinking (Akinci & Sandler-Smith, 2013). The practice focuses on a subject measurement and diminishes the role of objective assessment (Akinci & Sandler-Smith, 2013). Dane, Rockmann, and Pratt (2012) argued CEST is not applicable to the conscious execution of systematic problem solving. Intuition lacks precision as a problem-solving instrument and may result in extreme judgment errors (Dane et al., 2012). Moreover, the ability to offset the imprecise attributes of CEST may depend on an analyst's level domain expertise (Dane et al., 2012).

Cognitive experiential self theory in leadership practices. Individuals using the CEST model for data analysis may invoke the self-associative aspect infuses introspect for problem solving. CEST is useful as a predictive tool to identify competent and ineffectual leader's strategies (Curtis & Lee, 2013). Furthermore, Chaston and Sadler-Smith (2012) noted that a lack of technical knowledge or cognitive abilities is not the cause of inadequate leadership. Flawed interpersonal strategies outweigh the existence of a manual skill set (Chaston & Sadler-Smith, 2012). The success of a BI is dependent on leadership's ability to exercise interpersonal skills, and requires the management of personnel with attuned cognitive abilities prone to egotism, to promote accurate intelligence (Curtis & Lee, 2013).

Leaders might improve rational system functions serving the knowledge base and abstract problem-solving skills of subordinates through selective dialog (Curtis & Lee, 2013). Affect shares a close relationship with experiential system processes and inappropriate discourse could reduce the effectiveness of analyst (Curtis & Lee, 2013). When leadership provides an environment inclusive of a training program to assist personnel with the development of a meta-cognitive strategy to negotiate failures, analyst experience personal growth and improve core competencies (Carroll et al., 2015).

Daily operational tensions and stressors strain the affective and cognitive reasoning powers of an analyst (Curtis & Lee, 2013). Complex analysis strains the physical constitution of an individual, diminishing rational processing skills. The task of a leader is acknowledging and tempering the burdens of analysis requiring high-capacity conscious thought (Neuert & Hoeckel, 2013). Leaders must provide a balanced environment to capitalize on the intuitive and logical solution skills of analyst (Curtis &

Lee, 2013). Effective leadership programs include personal reflection elements to encourage problem resolution through peer discussion. The practice of reflection extends to leadership best practices, defining the qualities of a superior problem solver and decision maker. The management role of leadership, as the position relates to the cognitive and affect attributes of CEST, is critical to establishing a relevant BI framework (Curtis & Lee, 2013).

Leadership may use a psychological self-report instrument (i.e., REI) to identify personal cognitive style and the style of each subordinate analyst. Assessing a person's inclination toward demanding cognitive activities (need for cognition), or feeling and intuition (faith in intuition) to make decisions is vital to job pairing (Neuert & Hoeckel, 2013). A correlation exists between the structure of a problem and the appropriate selection of a reasoning style. Intuitive reasoning is an effective method for unstructured problems, while rational analysis is more efficient for structured problems (Neuert & Hoeckel, 2013).

Each analyst, data manager, and leader should complete an REI to assist with categorizing the individual's mode of information processing information (Curtis & Lee, 2013). A person will favor experiential (i.e., intuitive or implicit) reasoning, or rational (i.e., analytical, explicit, or effortful) reasoning (Curtis & Lee, 2013). Akinci and Sadler-Smith (2013) argued an individual's level of self-awareness as the matter relates to intuitive and analytical cognitive styles may manage emotions better and exercise metacognition effectively.

Leadership can aid the decision-making process by establishing problem-type categories to provide analysts guidance (Neuert & Hoeckel, 2013). Constructing category types will assist leaders with the delegation process, specific to the selection of reasoning style. The use of intuitive processing must remain well defined to resist the perception that decision-making occurs as a matter of random choice (Neuert & Hoeckel, 2013). Gentry (2014) stated a gap in definitive literature relating to leadership's effect on the success and failure of data analytic systems exists. Business and government agency BISs require leadership with the ability to manage human resources and an understanding of the concept needed to transform raw data into intelligence (Marrin, 2012a). The IC is an essential function of the BIS, with numerous vulnerabilities introduced by human error, flawed data, and environmental influences (Harrison et al., 2015). The selection of a data analysis method for information development is a fundamental decision, and the catalyst for IC success or failure (Wu, 2013). The transformation of information into knowledge occurs as BIS managers and analyst apply cognitive and experiential skills in CBR, RBR, or multivariate reasoning to process data (Neuert & Hoeckel, 2013). Organizational leaders may apply CEST principles to establish the best practices needed to implement BISs for effective resource management (Akinci & Sadler-Smith, 2013).

Contrasting decision-making theories. In addition to CEST, other formal decision making theory exist, with expected utility (EU) theory identified as the most popular (Stiegler & Tung, 2014). Developers of EU theory speculated humans make decisions by assessing levels of probability and benefit from choice (Buchholz &

Schymura, 2012). A disadvantage of EU theory was assumption the decision-makers possessed the capacity for probabilistic logic for all potential choices and consequences in a well-organized manner (Stiegler & Tung, 2014). Due to incomplete data and outcome uncertainty, EU theory has limited application in a real-world business decision-making environment (Stiegler & Tung, 2014). Further, decision-makers operating under risks encounter paradoxes and anomalies, causing them to abandon the axioms of EU theory (Buchholz & Schymura, 2012).

Additional alternatives to CEST also included the Bayesian static probability theory and the formalized pattern-matching theory. Stiegler and Tung (2014) stated by employing an adaptation of the Bayesian and EU theories of concepts, decision makers may include new information to modify the probability of a decided outcome. As a part of the decision-making process in business, application of the Bayesian probability theory requires expert knowledge or historical data to form an accurate conclusion, and may result in errant or subjective opinion by an analyst (Rigoux, Stephan, Friston, & Daunizeau, 2014). Moreover, the Bayesian theory approach involves multiple parameters operating in tandem (Rigoux et al., 2014). The Bayesian theory is inappropriate for this qualitative case study due to over fitting, because the data cannot be verified independently using external sources increasing the potential for errant outcomes.

Stiegler and Tung (2014) identified the use of the formalized pattern-matching theory in decision making, as a method to cope with limited statistical information and utilize the remarkable intuitive human ability to provide the meaning of information by identifying patterns. The capacity to analyze multifaceted or unstructured information is attributable to a person's ability to process information in a bi-directional, interactive system by accessing conscious and preconscious levels of the mind (Cerni et al., 2012). The concept of pattern matching, an inherent intuitive human ability, is reliant on the experiential context possessed by the analyst, and subject to error in the absence of adequate comparative data from learned experiences (Stiegler & Tung, 2014). Further, the concept of formalized pattern matching is subject to error in the absence of adequate comparative data from learned experiences, rendering the model inappropriate for this study. The selection of CEST over formalized pattern matching and the Bayesian static probability theories involved an understanding that data analysis often requires the use of multifaceted and convoluted information to advance information and resolve problems in dynamic situations.

Leadership

An individual's ability to retain conceptual knowledge, grasp organizational principles and procedural guidelines, and possess the ability to apply information in contextual situations defines a leader's value (Hendriks & Sousa, 2013). Competent leaders link success and business through action (Parris & Peachey, 2012). Moreover, Hoppe (2013) proposed that business leadership is a process of coordinating the mental environment, rather than the physical situation. An environment where business decisions occur in a vacuum at the top of the organizational chart is no longer effective (Hoppe, 2013). Establishing a defined role for qualified BIS leaders is vital to the success of organizational strategy, and minimizes the potential failure of the IS (Farrokhi & Laszlo, 2013). Leadership best practices should involve the conception and articulation of organizational goals, uniting of subordinates, and preventing a preoccupation with petty conflicts, all for the purpose of resource management (Molloy & Barney, 2015).

Leadership best practices. Best practices are measurable and teachable (Bloom, Eifert, Mahajan, McKenzie, & Roberts, 2013). Examples of best practices include a contextual application of quality control, inventory management, and the management of human resources (Bloom et al., 2013). Further, leaders using best practices understand organizational goals, promote a team environment, and possess the ability to self-development in a BIS environment (Gurses & Kunday, 2014). The capacity to learn from experience and invest the knowledge in associates is evidence of leadership best practices (Gurses & Kunday, 2014). According to Bloom et al. (2013), a strong association exists between the execution of best practices and higher productivity.

If leaders do not apply best practices during an organizational performance evaluation, incorrect assessments of intelligence analysis techniques may occur, resulting in errant or compromised decision-making (Marrin, 2012a). Data managers lacking best practices with minimal training, experience, or guidance perform data analytics based on trial and error (Serban, Vanschoren, Kietz, & Bernstein, 2013). Moreover, using decision makers to evaluate the quality or accuracy of intelligence analysis within the IS framework is problematic during the IC (Marrin, 2012a).

Bauer et al. (2013) stated that absent cognitive influence, leaders form decisions using two types of information: experiential and numeric. The experiential factor involves problem resolution using knowledge gained through experience. Using the information derived from statistical reports to solve problems is an example of numeric reasoning. Bauer et al. (2013) further posited that favoring one type of data to the exclusion of another might cause biased decisions and render sub-optimal outcomes. The employment of CEST requires orthogonal constructs for data analysis to increase the probability of accurate conclusions (Akinci & Sadler-Smith, 2013).

The perceptions of the decision maker, particular to preconceived outcomes, may create a decision-making bias influencing the evaluation of data (Marrin, 2012a). Utilizing systems thinking among organizational management encourages the development of free thought by leadership to troubleshoot BIS issues, without the encumbrance of the surrounding events and details experienced by decision makers (Skaržauskienė & Jonušauskas, 2013). BIS administration requires engaged leaders to offer support and commitment to staff implementing an organizational plan (Farrokhi & Laszlo, 2013), and the establishment of a management control system (Jamil, 2013).

Prior to the implementation of BISs, the establishment of a management control system (MCS) structure is vital to leadership system performance evaluations (Jamil, 2013). Per Jamil (2013), a MCS serves the function of measuring the capacity of an organizational strategy to gather, absorb, and leverage new information; a process described as absorptive capacity. Absorptive capacity attributes are an indicator of organizational framework and leadership's ability to establish the technological infrastructure needed for a BI (Jamil, 2013). Further, absorptive capacity reflects management's knowledge and skill with a correlation to the potential assimilation of BISs. Managers that focus on gaining a broad overlapping knowledge of organizational requirements, a profound understanding of the implementation strategy, and interpersonal skills exhibit core MCS competencies (Jamil, 2013). Keung and Shen (2013) argued the possession of any skill set is not sufficient to define the effectiveness of a manager. Instead, Keung and Shen (2013) stated, the application of a leader's skills are the catalyst for becoming an effective HR manager.

Learned consequences influence the decision-making process of individuals (Akgün & Keskin, 2014). Akinci and Sadler-Smith (2013) determined that an individual's cognitive style has a direct correlation to their critical leadership skills, including decision-making, interpersonal communication, and team building. Optimizing business training and development programs focused on best practices involves assessing and incorporating the individual cognitive styles of employees and leaders (Akinci and Sadler-Smith, 2013). However, Dane, Rockmann, and Pratt (2012) explored the use of intuition in conjunction with analytical decision-making, and determined organizations that use the cognitive data analysis style have the highest potential for affecting change in a Big Data environment. Furthermore, Dane et al. (2013) established a correlation between groups with an elevated level of domain expertise, and the use of experiential intuition as an effectual analytic tool for decision-making. The ability to create a data analytic strategy capable of rapidly transforming information into knowledge with accuracy must include the experiential and rational analytics core principles of CEST (Dane et al., 2012).

The uses of experiential and rational decision-making processes similarly serve leaders and data analysts to develop problem resolution skills (Dane, Rockmann & Pratt, 2012). Moreover, Neuert and Hoeckel (2013) postulated that effective business leadership must avoid slow, ineffective decision-making processes. Understanding the characteristics of problems influencing the analyst's decision-making process may facilitate the development of improved reasoning strategies. Furthermore, Neuert and Hoeckel stated that when faced with complex problems, data analyst exhibited an increase in accuracy with the use of intuitive judgment. Neuert and Hoeckel determined the development of an application-oriented approach to annualize data, inclusive of intuition, might allow companies to make rapid decisions in a fluid business environment. Leadership must exhibit best practices, by understanding the mental processes related to reasoning and problem resolution to administer effective BIS (Hoppe, 2013).

Human resource management. Human capital is essential to BI success and decreasing the time and cost of transforming information into knowledge (Gurses & Kunday, 2014). Information technology businesses that focus on the existence of experts, professionals and knowledgeable workers experience overall increases in performance. Organizations heavily invested in human capital exhibit elevated levels of performance, well above the norm. An essential component of resource management is leadership best practices, allowing administrators to recognize the value of human capital as an intangible resource vital to the sustainability of the organization (Gurses & Kunday, 2014).

Business leaders view HR as essential to overcoming knowledge management challenges (Nandita, 2013). Employing an educated workforce with a similar vision creates a favorable environment where an effective IC can thrive (den Hengst & Staffeleu, 2012). A 2012 industry assessment identified a workforce shortage of 190,000 workers with analytical expertise, and an additional 1.5 million data-literate managers in the United States (Geanina, Camelia, Apostu, & Velicanu, 2012). Furthermore, Geanina et al. (2012) stated the workforce shortage identified in the 2012 study inhibits Big Data initiatives focused on transforming information into knowledge. The capacity of an organization's leadership to manage human and non-human resources is essential to achieving sustainability goals (Molloy & Barney, 2015). Furthermore, organizational leadership's ability to form a comprehensive BI solution requires the coordination of internal and external resources (i.e., vendors, IT specialists, data managers, and organizational leadership), during the planning, implementation, and operational phases (Popovic et al., 2012).

Human resource factors contribute to a skilled workforce shortage. Minbaeva and Collings (2013) noted HR department architectures frequently lack best practice and standards to evaluate and recruit the talented human capital needed to fill developing strategic positions. The influence of a workforce comprised primarily of older workers creates a gap between the available personnel and qualified employees. Acknowledgment of the labor force issues relating to resource management caused organizations to prioritize recruitment in an effort to secure talented employees (Minbaeva & Collings, 2013).

The breadth and complexity of implementing BISs necessitate mandates from ranking officials in businesses and government agencies, with declarations strong enough to facilitate vital changes (Popovic et al., 2012). Business leaders have an expectation of accuracy regarding the transformation of information into knowledge (Geanina et al., 2012). Only 33% of leaders trust information derived from Big Data processing to form business decisions (Geanina et al., 2012). The inadequate development or identification of human resources occurs in IS environments (Anton, 2013). Chen et al. (2012), Evans and Kebbell (2012) argued that analysts need the skills required to convert raw data into knowledge and possess the ability to communicate gained intelligence to decision makers.

Knowledge management. Knowledge management is the result of a systematic approach to understanding the prerequisite skills needed to perform job tasks (Larsen & Olaisen, 2013). Knowledge management involves the training of skilled HR staff, adept at comprehending the role of data analysis and the benefits of accurately interpreting information (Nandita, 2013). Further, Nandita stated the mechanics of knowledge management requires data control systems to make valuable information available to the appropriate person in a timely manner. Three key dimensions comprise the foundation of knowledge management: (a) whom to share, (b) how to share, and (c) what to share (Nandita, 2013). Leaders of knowledge management programs must control the distribution of intelligence, by matching the need for information with organizational member's tasks and goals (Nandita, 2013). The *whom to share* dimension requires decision makers to develop a plan of discernment to distribute information on an internal and external organization basis (Nandita, 2013). Information deemed to possess a value for improving quality, pattern recognition, minimizing cost, and producing a faster response to consumers' needs composes internal sharing (Ndinguri, Prieto, & Machtmes, 2012). External sharing includes elements necessary to improve information quality, pattern recognition, cost reduction, and improve responses to stakeholders. Mason and Simmons (2014) stated that the category of stakeholders is more than investors, customers, and employees. Instead, the term stakeholder is more expansive and includes groups and entire communities, with service expectations (Mason & Simmons, 2014). Leaders must select *how to share* knowledge by using a method to inform and update information consumers without providing redundant information (Ndinguri et al., 2012). Moreover, leaders establishing a plan to distribute knowhow and best practices to subordinates are central to the theme of *what to share* (Nandita, 2013). The systematic approach to knowledge management requires skilled human capital resources for data control and sharing to achieve proficiency (Nandita, 2013).

The ability to perform particular BIS jobs competently is dependent on an individual's knowledge and skill sets (Deng & Chi, 2012). According to Evans and

Kebbell (2012), the desire to improve job performance and pride in work products are intrinsic to high functioning data analyst. Despite the latter, when data analysis outcomes are faulty neither the analyst, nor the decision-maker identifies the basis for the resolution (Gentry, 2014). Moreover, the integrity of ICs requires continuous evaluation, incorporating the analyst as a component of the system examination to analyze functions and identify the potential for errors (Gentry, 2014). Errors by BIS decision-makers risk the safety and security of stakeholders (Perry, Wiggins, Childs, & Fogarty, 2012).

Proficiency in decision-making is necessary and difficult to achieve (Perry et al., 2012). The complexity and time sensitive nature of ICs often form a dynamic situation requiring expedited decision-making. Employing personnel with the ability to shift the resolution criterion based on the situation, is advantageous to a company and by extension beneficial (Aminoff et al., 2012). Moreover, a direct link exists between decision criterion, memory recognition and performance (Aminoff et al., 2012). Expert decision-makers possess a superior capacity to compensate for a normative BI strategy and provide decisions with an increased level of accuracy (Perry et al., 2012). Individuals with the ability to adapt in a fluid work environment were more successful, compared to counterparts without flexibility in assigned tasks, regardless of experience or knowledge deficiencies (Aminoff et al., 2012). Perry et al. (2012) ascertained computer-based decision support systems (DSS) did compensate for the lack of workforce experience in the information acquisition phase of BISs.

Improper data acquisition wastes resources and causes distractions or misdirection for decision makers (Bärenfänger, Otto, & Österle, 2014). Faster decision-making, not the speed of information processing, is the goal of BISs (Bärenfänger et al., 2014). Amara, Soilen and Vriens (2012) suggested leadership should understand data collection, the interim steps of analysis, and the correlation of data provenance to prequalify the value of information. The framework of an IS is inherently unstable, ever changing and complex, increasing the level of difficulty and demands leaders encounter (Coyne, Bell, & Merrington, 2013). Comprehensive data collection is not enough. Organizational leadership must contemplate data collection criteria and the potential uses for information to meet strategic BIS goals (Ramakrishnan et al., 2012).

Intelligence Cycle

An IC is a systemic application of disciplines requiring the transformation of data using a deliberate architecture to minimize analysis vulnerabilities to produce actionable knowledge (Bartes, 2013). Used synonymously with Intelligence Process, the IC concept is centuries old (Agrell, 2012). A simple IC includes data collection, analysis, and decision-making functions linked together to form a process (Phythian, 2013). Categorized as an endless chain of functions, an IC only performs to the optimal level afforded by the most inefficient service (Phythian, 2013).

The purpose of an IC is to transform raw data into knowledge for use by decision makers (Zeng, Li, & Duan, 2012). The transformation process, universally described as BI, occurs as a series of events furthered by data analysis (Zeng et al., 2012). Predictive outcomes are achievable by using an appropriate data analytic style (Cox & Jantti, 2012). Wu (2013) stated the cultivation of intelligence from raw data requires a cyclical process that includes phases of assessing stakeholder needs: (a) planning, (b) data collection, (c) evaluation of information, (d) data analysis, (e) production of intelligence, and (f) dissemination of knowledge for action. Chen et al. (2012) and Den Hengst and Staffeleu (2012) stated that businesses incorporating a centralized information organization strategy, employing highly educated people sharing a similar vision, created an environment where the IC thrived. Furthermore, the use of proper data collection, data analysis techniques, business IC, and decision support systems expedite the information chain providing actionable intelligence (Chen et al., 2012). Although data forms the foundation for ISs, information unique to e-commerce, government, science, health care, and security and public safety may require domain-specific analytics for accurate parsing (Chen et al., 2012). The capability to achieve the correct parsing of information requires IT tools (Den Hengst & Staffeleu, 2012)

According to Sangar and Iahad (2013), an organization's IT solutions must support BIS functions to capitalize on critical success factors. Whether ad hoc or systematic in architecture, BISs share a common objective to refine information into intelligence for use in decision-making (Sangar & Iahad, 2013). The collection of information from suitable sources is cultivated and enriched using an appropriate analysis method, providing actionable intelligence (Sangar & Iahad, 2013). The efficiency of a BIS influences the value of actionable intelligence (Phythian, 2013).

Organizational intelligence cycles. Understanding BISs in the information systems era is a core component of business competencies, and necessary for the construction of a sustainable business design by organization leaders (Hoppe, 2013; Nandita, 2013). The BI market continued to expand and by 2011, 10.7 billion dollars was invested in the development of IT functions and developing capabilities globally (Zeng et al., 2012). In the global market, successful applications for BI include conventional and contemporary business models that affect the sustainability of organizations (2012).

On a micro level, members of the healthcare industry are dependent on IT to improve operating efficiency and increase patient safety (Ashrafi, Kelleher, & Kuilboer, 2014). In 2001, the Institute of Medicine administration called to action hospital administrators and physicians to improve record keeping through computerization of orders and archival databases to improve patient safety. An implementation of the noted IT laden practices directly affected healthcare providers and hospitals finances. Members of the healthcare industry implemented key components of the BI cycle to increase efficiency and control expenditures by transforming information into actionable knowledge. Further, Ashrafi et al. (2014) stated the BI cycle implementation increased the value of clinical and administrative data, without a substantial investment in a health information technology infrastructure. Moreover, aligning information management philosophies with an IC strategy, may allow administrators to reduce waste, improve patient safety, and rapidly produce policy drivers (Ashrafi et al., 2014).

On a macro level, organizational leaders continue to refine the BI cycle to gain a competitive advantage. The establishment of a free-trade zone, due to a proprietary partnership, and cooperative agreement with the European Union, Tunisia is poised to become an international economic power (Nasri, 2011). Narsi examined six businesses functioning in different sectors across Tunisia, and determined that locating reliable information to support the BI cycle is fundamental to the success of each organization. Further, Narsi stated predominately internal, rather than external, intelligence sources yielded the greatest actionable intelligence. However, the ability to drive knowledge into action requires an organized infrastructure. Narsi argued unorganized BIS structures were common in Tunisia, especially in burgeoning ICs. A structured environment with supporting policies increases the probability of maintaining a competitive IS (Nasri, 2011).

Ellis (2013) described business intelligence as a decision model, where data drives the decision support process, improves efficiency, and enhances the effectiveness of a project. A failure in any of the IC functions may negatively influence the profitability of an organization (Tallon, 2013; Bartes, 2013) and competitive advantage (Roberts & Grover, 2012). Organizations must analyze multiple sources of data systematically, prioritizing problems for resolutions, to exploit the value of intelligence (Lowe & Innes, 2012; Nag & Gioia 2012). Selecting the proper BI framework aids companies in strategic development and increases efficiency (Harrison et al., 2015).

Government agencies intelligence cycles. The conventional use of BISs served corporations as an aid to forecast stakeholder interest by analyzing collected information relating to customer needs and product rating (Demirkan & Delen, 2013). Copeland et al. (2012) researched BI models and stated the complex chain of tasks composing BISs, are universally applicable to private business and government agency goals. Different BI models exist with similar purpose, providing intelligence for decision-making by extracting information from raw data stored in relational and multidimensional databases (). Through the implementation of an enterprise strategy, BI models are useful to government agencies, supporting decisions at all levels of an organization ().

Evans and Kebbell (2012) argued contemporary government agencies are utilizing traditional business models to manage stakeholder expectations. Fiscal cuts and increased media attention require government agencies to operate efficiently and manage a brand standing (Evans & Kebbell, 2012). Businesses and county government agencies are utilizing business models to plan IS frameworks designed to meet needs of stakeholders. Government and business leadership focus on elements aligned with Total Quality Management and other force factors observed in public and private sector environments (Carter, Phillips, & Gayadeen, 2014).

Essential to an effective government IS is a centralized authority overseeing the management of information (Sahin & Matusitz, 2013). Pee and Kankanhalli (2015) asserted government organizations with proactive roles in developing policies to improve information sharing, demonstrated the most desirable performance enhancement increases. Moreover, performance outcomes included decreased production times, reduced backlog, and improvement in processing efficiency (Pee & Kankanhalli, 2015). Government agencies will only succeed at meeting goals by promoting the uninhibited flow of information and interagency collaboration (Schnobrich-Davis, 2014).

The cooperation of leadership is an essential factor in allowing information to flow effectively between multiple government agencies beyond jurisdictional boundaries (Steden, Wood, Shearing, & Boutellier, 2013). The dynamics of a county government require the trading of information with other administrations to exploit intelligence and identify patterns. The selection of a proper technological solution and training program is imperative for the creation of a permissive environment for analysis and the identification of patterns (Steden et al., 2013). Phythian (2012) established that regardless of the selected analytic discipline, IC interruptions affect stakeholders.

Intelligence cycle challenges. In the information technology era, digital technology influences every business group and organization (Liu, 2013). The rapid increase in information production has expanded the demand for data processing (Tallon, 2013). Xindong et al. (2014) cited the creation of 2.5 quintillion bytes of data daily, with 90 percent of all the existing data in the world produced between 2010 and 2012. The expansion is equal to a data volume 60 million times greater than the content stored in the U.S. Library of Congress (Hilbert, 2012). Projections suggest data collection has a potential growth rate of 40% annually (Tallon, 2013). The number of platforms available to individual users, businesses, and governments to view and analyze data increased substantially within the last decade (Geller & Drachsler, 2012). Delimiters of Big Data include the quantity of information received and stored, rate of information production, complexity of the data source, and distribution to end-users (Louridas & Ebert, 2013). The failure to implement an adaptable IS strategy, capable of compensating for substantial influxes in data, will result in the loss of actionable intelligence (Louridas & Ebert, 2013).

The use of Big Data to develop intelligence influences an organization's competitive advantage (Liu, 2013). Even with advancements in technology, companies still struggle to assign value and meaning to stored data (Liu, 2013). Assigning value to information occurs differently based on the decision criteria applied by organizational leaders. While Louridas and Ebert (2013) identified set limits for the storage of information, Huang and Rust (2013) explained multiple data sources define the value of Big Data by size, variability, and complexity. Companies must examine the value of the data to assess the return on investment, which includes the cost of data collection, analysis, and storage of mined information (Tallon, 2013). Two frequent challenges encountered by organizations are the diversity of collected data and the appropriate selection of analytic processes (Tallon, 2013). A crucial element for creating a successful information system in a Big Data environment involves the improvement of data and task parallelism, and support of vertical and horizontal computation parallelism (Tallon, 2013).

George, Haas, and Pentland (2014) reviewed the processes necessary for effective and efficient collection, retention, and analysis of data. A key aspect related to proficient information system processes relied on the accurate defining of informational needs and characteristics of the collected data, to develop ethical practices. In a Big Data environment, revisions to data management procedures ensure that collection and storage policies align with organizational strategic requirements (George et al., 2014). Moreover, George et al. stated accurately defining information systems management policies and procedures minimize data storage vulnerabilities.

Corporate leaders view Big Data as a tool for marketing and product development (Wigan & Clarke, 2013). Similarly, government agencies use Big Data for strategic and predictive planning (Steinhoff & Carnahan, 2012). However, the unethical use of Big Data has consequences. Businesses and governments occasionally ignore the potential risk to minority groups, when the collection of valuable data benefits the majority (Wigan & Clarke, 2013). The adverse outcomes of improperly handled Big Data can affect individuals, social groups, and government entities (Wigan & Clarke, 2013).

Intelligence cycle vulnerabilities. The distinct attributes and business strategy of an organization frame IC vulnerabilities. According to Jenster and Soilen (2013), organizational designs include the structural characteristics of defenders, prospectors, analyzers, and reactors. Businesses must create an intelligence structure aligned with the organizational leadership’s, implicit or explicit, IC strategic goals. Harrison et al. (2015) emphasized the significance of structure to minimize IC vulnerabilities during BIS implementation. Weaknesses in ICs include unidirectional communications, lack of support regarding meta-data management, and lack of operational data stores. Moreover, the absence of sufficient structure encourages problems relating to the proficient sharing of information. Ong et al. (2011) stated that five major layers comprise appropriate BIS architectures to form an IC: (1) data source, (2) extraction, transformation and loading; (3) metadata, (4) data warehouse, and (5) the end user. Establishing a BIS with these five layers of architecture may ensure data output of sufficient value for use by leaders in decision-making processes.

Ong et al. (2011) described the data source layer as a composition of information developed within the organization and data originating from an external source. The differentiation between the origins, whether internal or external, is critical to the extraction, transformation and loading of data to identify and collect relevant data from different sources. The metadata layer is data-about-data, offering a link between information by providing context through correlation (Ong et al., 2011). The data warehouse layer involves the process of storing data based on a subject matter, storage based on collection time, and the need to maintain information without inadvertent change. In the end user layer, BIS leaders disseminate intelligence using a variety of tools to display information in different formats. Organizational leaders employing a proper BIS architecture reduce IC vulnerabilities (Ong et al., 2011).

Beyond the scope of architectural design flaws, several general factors render ICs ineffective; human resources, data management, and organizational change (Amara et al., 2012). As a positive affect tool, knowledge gained from an effective IC provides business and government agency leaders with the information needed to serve stakeholders (Popovic et al., 2012). The speed or quantity of information produced using a BIS is not an appropriate measure of success. Quantifying the worth of any BIS occurs through an examination of the information value chain; the time and effort spent to link raw data, information, and knowledge for use in decision-making (Popovic et al., 2012).

Popovic et al. (2012) argued that to achieve success, business leaders must integrate intelligence into all business processes to improve decision-making and fulfill stakeholder expectations. Isık, Jones, & Sidorova (2013) stated the BIS selected by leaders must match the problem space or decision environment to prevent vulnerabilities. Furthermore, a failure by leadership to rely on strict operational guidelines governing BIS functions, results in data analysis deficiencies and the potential misinterpretation of analysis outcomes (Popovic et al., 2012). Managers that do not understand the business processes supporting an IS and hardware infrastructure diminish information quality, reduce BIS maturity, and subsequently render an IC ineffective (Popovic et al., 2012). Moreover, the decision-making environment created by organizational leaders moderates the success BISs (Isık, Jones, & Sidorova, 2013).

Advancements in Intelligence Systems

The human race is dependent on the collection and interpretation of data (Boyd & Crawford, 2012). The nature and philosophy associated with information handling form the future of the world (Leeper, Richter, & Walker, 2012). The production of large volume data at an accelerated pace creates benefits and challenges for processing, managing, and applying intelligence (Boyd & Crawford, 2012). Each challenge associated with the collection and transformation of Big Data into knowledge has an intrinsic affect on ICs and the encompassing BISs (Leeper et al., 2012).

New inventions encounter resistance before gaining a level of acceptance (Rivard & Lapointe, 2012). With respect to IT, employee resistance to implementing policies may serve the function of problem identification, promoting further change, and providing a corrective value during the development process. The value of resistance diminishes as opposition leads to organizational dysfunctional (Rivard & Lapointe, 2012). Evolutions in IT promoted advancements in IC disciplines, and caused practitioners to consider the actions of a population as a collection of facts waiting to have context assigned (Rasanen & Nyce, 2013).

Hallmarked by the rapid transformation of information into knowledge, ICs present challenges for government agencies (den Hengst & Staffeleu, 2012). Bureaucracies associated with conventional government models inhibit the ability to exploit the value of actionable knowledge. The implementation of an intelligence driven model requires organizational change and an adjustment to a plan of action influenced by cultivated knowledge (den Hengst & Staffeleu, 2012). Technology drives the speed of information production, collection, and analysis. For example, Summerville and Dai (2012) proved a competitive advantage was obtainable through proper data management. Data management specific to IT initiatives must conform to organizational requirements, strategies, and business and government models. Further, forecasting opportunities that IT innovations may provide, and investing in the future to secure a competitive advantage is the responsibility of organizational leaders (Summerville & Dai, 2012).

Ramakrishnan, Jones, and Sidorova (2012) identified an isomorphic relationship between organizations and the use of BI to achieve operational consistency. A link exists between achieving operational consistency, and the operation of a comprehensive BI data collection strategy (Ramakrishnan et al., 2012). However, technological innovation presents challenges. Overcoming obstacles introduced by IT advancement, by adapting and changing policies and procedures as necessary may define the success of organizations utilizing BISs (Chadhuri, Dayal, & Narasayya, 2011). George et al. (2014) argued concurrent revisions to an organization’s information system management practices and procedures ensure transformed data aligns with operational needs.

Data Intelligence Systems Value

Substantiated data has a definable value as a commodity for businesses (Summerville & Zong, 2012). Evans and Kebbell (2012) and Rasanen and Nyce (2013) stated information has a depreciable value. Utilizing intelligent information in an expeditious manner capitalizes on the value of knowledge (Amara et al., 2012). However, sacrificing the quality of intelligence to expedite DSS operations is not a strategically prudent practice (Amara et al., 2012).

Kowalczyk and Buxmann (2015) observed that maintaining the quality of intelligence begins with the information source. Geller (2012) cautioned the greatest downfall of any dataset analysis model is the tendency to predetermine the value or accuracy of all collected information. Data flaws include untrustworthy information, bias analytic assumptions, and computation errors (Shull, 2013). When unidentified errors exist, data may yield faulty intelligence resulting in specious decision-making (Shull, 2013). An example of inadvertent and unidentified errant data could consist of data collections from two sources of varying reliability (Kowalczyk & Buxmann, 2015). The infusion of aberrant material into a reliable data flow poses issues with synthesizing, refining, and standardizing the information for additional BI task challenges. However, efficient and accurate data loading are indispensable to the success of BISs (Kowalczyk & Buxmann, 2015).

Leaders must evaluate individual data types singularly and as a whole to improve the efficiency of BIS (Geller, 2012). Changing a leader's focus will allow a company to optimize advantages of the BIS in less time, and enable the organization to stay competitive in a malleable business environment (Geller, 2012). Managers need to assess and categorize information (Bärenfänger et al., 2014). Certain information may contain knowledge of greater value, making prioritization in data analysis a fundamental practice requirement. Kowalczyk and Buxmann (2015) and Bärenfänger et al. (2014) stated information source selection is imperative to the efficiency of data flow, and the ability to provide a refined product to the decision support system of the BIS.

Shull (2013) hypothesized data analyst spend significant time sifting through large volumes of data with disqualifying flaws, diminishing or nullifying the anticipated value of the information. Bärenfänger et al. (2014) argued that gathering the information truly needed for proper analysis allows managers to make faster decisions. Wigan and Clarke (2013) deduced the enthusiasm of leadership and gatherers to collect information overshadows the need to compile quality data from discriminate sources. Qualitative or quantitative information, obtained from suitable sources, is necessary to serve key intelligence functions defined by leadership (Sangar & Iahad, 2013).

Organizational strategies must include information quality assessment as part of an overall digital technology design to remain competitive (Pankaj, Viswanath, & Supreet, 2013). Safeguards may minimize statistical errors associated with flawed data. Errors are preventable with the inclusion of standardized methods in data analysis (Wigan & Clarke, 2013). Ji et al. (2012a) emphasized the need to include the insight of individuals with domain expertise in data clustering to improve the accuracy of analysis and the subsequent reporting analytics. The proper structuring of heterogeneous human capital, specific to analysis styles, influences the effectiveness of an IC and reduces the probability of flawed outcomes (Phythian, 2013).

Data Analytics

Predictive analysis allows all industries to forecast future actions of stakeholders (Gold, McClarren, & Gaughan, 2013). Key factors in developing a reliable predictive model for analytics require a framework capable of accounting for existing iterative and fluid dynamics, and incorporate new data as the information becomes available (Gold et al., 2013). Wu (2013) stated data analytics and processing in an IC involves (a) problem specification, (b) planning and direction, (c) collection of information, (d) processing information, (e) data analysis, and (f) dissemination. First, the process of cultivating actionable intelligence begins with the *problem specification*, permitting leaders to *plan* for the collection of raw data from appropriate sources (Wu, 2013). Second, BIS leaders must design a direction for analyst to follow for researching the problem, analyzing data, and completing articulate reports for decision-makers (Phythian, 2013). Third, after leadership completes the planning and direction phase of the IC, personnel must collect raw data. Fourth, post collection, data analysts' *process information* to achieve validation and data representation (Phythian, 2013). Through data cultivation using human data analytics or artificial intelligence tools (i.e. computers and software), information development tasks are accomplished (Wu, 2013). The fifth action, *analysis*, is the transformation of raw data into knowledge requiring data analyst to provide contextual meaning for all collected information (Phythian, 2013). The sixth and final step is *dissemination* of intelligence to the decision-maker. Concerns relating to the use of automated tools for analysis exist. Artificial intelligence tools adapted for use with BISs are imperfect and lack the combination of cognitive and experiential reasoning humans possess (Wu, 2013).

Data analytics is a distinctive and deliberate step in the IC. Wu (2013) examined the curricula of 27 institutions offering professional tradecraft and domain intelligence education courses. Although all of the institutions provided instruction on data collection, only three explicitly or implicitly included intelligence information-processing elements.

As argued by Wu (2013), the benefit of an education in information processing competencies strengthens an intelligence analyst's ability to process larger volumes of information proficiently. In a collective environment, similarly trained analysts possess the capacity to share knowledge with an increased speed and accuracy, improving the general performance of an intelligence group (Chen et al., 2012).

ISIS practitioners utilize knowledge organization systems (KOS) to enhance information-processing competencies (Wu, 2013). The analysis and interpretation of raw material with a goal to organize and represent concepts, and documents describes the function of a KOS. The proper operation of a KOS allows users to cultivate intelligence from raw data and then fuse the insight into meaning, forming interrelated concepts. Organizing intelligence furthers the ability to share knowledge with internal workgroups and external organizations (Wu, 2013). Organizational leaders recognize the advantages of the outcomes associated with CBR, rule-based reasoning (RBR) and multivariate reasoning advanced data analytics (Apte, Dietrich, & Fleming, 2012).

Case-based reasoning. CBR is an extension of human rationale, applying learned experiences to assess new situations or solve problems (Marling, Montani, Bichindaritz, & Funk, 2014). The word case, in CBR, denotes a single episode or occurrence of a problem, a solution, and the resolution (Marling et al., 2014). As a sustainable value process, CBR is a collective of four critical steps: retrieval, reuse, revise, and retain. The retrieval action requires the practitioner to match the current problem with a previous case in their personal memories. Marling et al. further stated the implementation of the most relevant solution should occur following an assessment of past solutions for application to the current case problem. CBR is a building process, with each episode stored for future retrieval, revision, and reuse. Marling et al. (2014) argued perspective analyst candidates should possess personal life experience applicable to problem solving. The use of CBR in rule induction or machine learning industries is common, and gaining acceptance and popularity in deductive reasoning domains (Marling et al., 2014).

Performance measurement is a priority for management personnel (Behzadian et al., 2012). Private and government leadership need effective tools to evaluate the performance of interests. Behzadian et al. (2012) argued that CBR forecasting is a valuable method to predict interest failure or success using inductive processes. Compared to the restrictive nature of deductive reasoning, the flexibility of CBR allows data analyst practitioners to operate under the assumption that previous experience is applicable to future situations. Moreover, CBR may provide superior results in environments with reoccurring themes; however, the unique nature of crises makes the analysis process unsuitable (Behzadian et al., 2012).

CBR is a data analysis methodology requiring the analyst to possess prior case knowledge to solve a problem (Sun, Li, Huang & He, 2014). A derivative of the cognitive science, information retrieval, reuse, revival, and retention comprise the foundation for CBR processing (Hu, Qi, & Peng 2015). The benefit of CBR to BISs is the continued engagement of human resources, to maintain a connection between contextual information and operative knowledge; supporting differing aspects of human reasoning

(Chang, Lee, & Wang, 2015). Li and Sun (2012) established CBR as an effective information-processing tool to aid leaders in strategic decision-making. Managers must reduce judgments' based on emotion, intuition, and unconsciousness influencers (Ghadami, Seyedhosseini & Makui, 2012). The use of CBR coupled with rational decision-making by organizational executives and leaders increases the probability of successful business choices (Li & Sun, 2012). Using CBR, managers may adapt previous solutions to a new situation, producing credible recommendations based on the experiences of organizational leaders (Ghadami et al., 2012).

Information systems managers encounter obstacles linked to supporting strategic decisions with long-term consequences (Ghadami et al., 2012). Businesses and government agencies seek ways to employ strategic decision-making to facilitate competitive advantage. Gaining a competitive advantage in business relies on the exploitation of an organization's primary resources and capacities (Ghadami et al., 2012). Executives assessing business problems categorize elements of a dilemma based on prior experiences and involuntarily create response patterns; an example of leadership utilizing CBR (Behzadian et al., 2012). An advantage for business leaders to apply CBR in problem solving includes filling gaps in knowledge and compensating for data containing uncertainty, by using prior experiences of similar context (Paikari, Richter, & Ruhe, 2012). Marrin (2012b) equated qualitative analysis, aligned with CBR, to the art of analysis based on intuitive process combining education, instinct, and experience. An individual's creativity as an analyst is critical and requires support and fostering by a collaborative group, including leadership (Marrin, 2012b).

According to Ji, Park, and Lee (2012b), real world problems have properties that are dynamic, independent, and unpredictable. CBR is applicable in different professional disciplines to aid DSSs. The use of CBR permits powerful management panels the capacity to take action when events are complex and uncertain, by using previous experiences. Ji et al. examined the use of CBR, paired with adaptation and candidate selection, to enhance cost models and guide decision-making processes by eliminating distortion. Inexperienced industry practitioners or individuals without the exposure to similar cases can use attributes of CBR to retrieve and qualify information proactively and project outcomes (Ji et al., 2012b).

Rules-based reasoning. The increased volume of data created in the technologically contemporary global market, expedited innovation and improved algorithms to process more data at an increased pace (Mooney & Roddick, 2013). Advocates of the scientifically based quantitative analysis method, Rule-based Reasoning (RBR), argue the impossibility of considering all variables during the analysis process (Marrin, 2012b). Data appears as sequences in either total or partial ordering, allowing observers to predict the next event in a sequence by using algorithms. Mooney and Roddick designed a data organization and processing criteria known as Sequential Pattern Mining (SPM). The SPM model has a transferable application for the study of criminal offender behaviors, goods and services market analysis, system failure prediction, and a plethora of other BIS uses (Mooney & Roddick, 2013).

Using the RBR method, analysts work to identify key variables and weigh the significance of each element, connecting known variables to offer a scientific conclusion (Marrin, 2012b). Scientific analysis assists analysts resolve the significance of information to structure outcomes (Marrin, 2012b). Kahn and Mohamudally (2012) identified robustness, scalability, and efficiency as benefits of RBR analytics. However, if the data flow is too vigorous, or the dataset becomes too substantial, the acquired knowledge could qualify as misleading intelligence (Kahn & Mohamudally, 2012).

Computer based DSSs rely on RBR, and organizational leaders employ technology to compensate for, and improve, decision-making skills of less experienced personnel (Perry et al., 2012). Haberman and Ratcliffe (2012) determined the predictability of increased public safety risks by implementing spatiotemporal pattern practices in data analytics. Moreover, Greengard (2012) explored the affirmative use of technology to perform predictive analysis for government functions, specific to legislative action, noting a U.S. city that experienced a 25% increase in public safety by using proactive measures afforded by intelligence driven policies. The combined methods of data analysis, software development, and predictive analytics may permit government agencies to perform proactive operations to influence public policies.

Multivariate reasoning. Marrin (2012b) argued that valuable intelligence work is a product of quantitative (scientific) analysis, coupled with intuitive and experiential analysis. Organizational leaders developing ISs use a combination of science and art to form a meaningful information analysis process. Without an automated DSS, unchecked human bias may influence final decisions (Winter et al., 2013). The multivariate behavioral approach offers a favorable design for predictive modeling (Winter et al., 2013). Zhao and Harrison (2012) established that multimodel analytics allow data analysis to occur in an informed and thoughtful manner. Kim, Lee, Woo, and Shin (2012) discovered by adding algorithms to the CBR method the accuracy of projections improve. The sole use of CBR may result in data analysis errors due to flawed reasoning (Ahmed, Banaee, & Loutfi, 2013). The advantages of multivariate reasoning include exploitation of incremental knowledge and generalizations, without duplicating results and amplifying robustness of noise (Joshi, 2012).

Companies must operate using a balanced decision method to remain competitive (Bauer et al., 2013). Bauer et al. explored biases that may exist in single method analysis, which may lead to faulty leadership decisions. When a leader possesses applicable experiences, they may make faster decisions resulting in systematic biases due to overconfidence. Bauer et al. argued the use of a heuristic process or method to analyze data might introduce bias based decision-making. Analysts conducting exemplar-based data analysis, mimicking previous observation with favorable outcomes, frequently introduce bias (Bauer et al., 2013). Reducing bias during data analysis may require the use of a statistical model to create a visual representation for multivariate data (Martínez, Márquez, Gunckel, & Andreani, 2013).

Summary of Literature Review

Visual analytics is a computer mediated visualization technique or tool used to maximize a human's capability to decipher conflicting and dynamic data (Kang & Stasko, 2012). The use of visual analytics creates an environment conducive to the collation of new information quickly (Andrienko & Andrienko, 2013). The problem of resolving information scalability issues are the responsibility of IS administrators. Kang and Stasko (2012) described the challenge of information scalability as the transformation of raw data into actionable intelligence using massive Big Data, with the added task of adapting outcomes for presentation and use by different audiences. The task of adapting outcomes for organizational leadership's presentation to stakeholders aligns with visual scalability problems, defined by the inability to represent massive sets of data in relatable terms visually (Kang & Stasko, 2012). Further, Armstrong et al. (2012) argued stimuli consistent with individual processing preferences produced greater engagement with the viewer, demonstrating a correlation between visual learning and cognitive processes.

Transition

Section 1 contains an introduction for the foundation of the study relevant to the problem and purpose statements, research question, conceptual framework, operational terms, the significance of the study, and review of the literature. Additionally, Section 1 includes an overview of the IC, data analytics, and CEST. Further, improvements to business practices, achieved by understanding the CEST perspective, may allow IS leaders to capitalize on the value of information and produce actionable intelligence using a delegation process based on the individual analyst’s reasoning style. Section 2 includes the (a) role of the researcher, (b) identification of study participants, (c) identification and justification of the research method and design, (d) population and sampling, (e) ethical research conditions, (f) data collection, (g) data analysis techniques, and (h) reliability and validity considerations. Section 3 includes a detailed presentation of the (a) research findings, (b) application to professional practice, (c) implications for social change, (d) and recommendations for action, (e) further study, and (f) reflections.

Section 2: The Project

Section 2 includes an outline of procedures used for this doctoral study and begins with a review of the purpose statement and a description of the project's methods and processes. Section 2 also includes the (a) role of the researcher, (b) identification of study participants, (c) identification and justification of the research method and design, (d) population and sampling, (e) ethical research conditions, (f) data collection, (g) data analysis techniques, and (h) reliability and validity considerations.

Purpose Statement

The purpose of this qualitative, single-case study was to explore the best practices needed by data management leaders to utilize BISs for effective resource management. The population consisted of county government leaders and data analyst in the eastern United States performing IS methodologies (ISM) within an implemented BIS. According to Ganzert, Martinelli, and Delai (2012), in an ISM environment, a systematic approach to decision-making involves each person contributing to IS functions, due to recursive processes. The results of this study may contribute to social change through the utilization of a government BIS framework to improve public safety policy development.

Role of the Researcher

As the researcher, I engaged in every aspect of this study, including the data collection. Researchers develop a meaningful understanding and personal identity associated with the study subject matter when they engage in all facets of the research (Berger, 2015). My private sector professional experience includes 7 years in the textile industry elevating to mid-level management and holding the title of Assistant General Manager. My duties involved interviewing employee candidates and managing organizational resources. Using a BIS model, I assisted in the implementation of a consumer care plan addressing customer problem resolution, Profit and Loss statement analysis and management, and a growth development strategy. Further, my public sector professional experience encompasses 17 years as a county government employee, which included more than 8 years as an investigator with over 200 hours of investigative and interviewing training. My investigator training included instruction in kinesics interviewing. Analysis, organization, and validation of all data occurred post-collection phase, while the study participants work at a government agency as analysts, data managers, and members of the IS leadership, I had no professional or personal relationship with the participants.

Using the Belmont Report protocol, including and not limited to participant confidentiality, obtaining informed consent, and the storing of data gathered during the study, I addressed the researcher’s responsibility to address ethical issues. After training provided by the National Institute of Health was completed, I received a Certificate of Completion for Protecting Human Research Participants, identifiable as Certification #997248. The study did not include the targeting of a vulnerable population. A qualitative researcher must demonstrate a practical understanding of conceptual knowledge relating to a code of ethics, and exemplify responsibility and integrity in research (Damianakis & Woodford, 2012). In addition, I minimized systematic errors and bias by following an appropriate research design, and using professional experiential knowledge to review the collected data. According to Gargon et al. (2014), using a deliberate research design to meet study aims mitigates researcher bias.

Using multiple data sources, member checking, and a well-designed interview instrument structured to explore the research question, I reduced bias during the study. Enhancing the accuracy and repeatability of the research data by avoiding bias is incumbent on the researcher, and requires the researcher to remain mindful of the need to prevent unnecessary personal influence (Malone, Nicholl, & Tracey, 2014). Attention to the initial interview instrument is necessary to assure the queries focus on the research question without biasing the participant (Gioia, Corley, & Hamilton, 2013). Furthermore, Petty at al. (2012) argued that researchers who use multiple data sources protect against bias. Reducing the potential for bias is the responsibility of the researcher and necessary to assure the validity of the study outcomes (Malone et al., 2014).

I implemented a semistructured interview instrument. Developing an interview protocol that aligns with the research enhances the quality of study results (Xu & Storr, 2012). Researchers use the semistructured interview process to elicit in-depth spontaneous answers from study participants (Rowley, 2012). Moreover, using the semistructured interview method, researchers may have an opportunity to explore insights arising from unplanned and instinctive responses given by the participants (Schatz, 2012). Researchers conduct interviews with an open-ended question format to elicit meaningful and culturally salient participant responses, rich and explanatory in nature (Stuckey, 2013). Furthermore, interviewers use open-ended questions and a semistructured interview technique to provide an environment for better communication (Andersen et al., 2012).

Participants

Eligible participants served either as leaders tasked with the implementation of a county government BIS, or worked as data analyst within the scope of control to transform raw data into intelligence. All participants (a) held a position within a U.S. based county government, (b) contribute to the function of the county government BIS, (c) and participated in a face-to-face interview. I interviewed four data analyst, and five IS administrators tasked with the responsibility of implementing a BIS.

Conscientious researchers are concerned the interpretive account represents the underlying group encompassed in the investigation (Frels & Onwuegbuzie, 2012). Establishing participant criteria to ensure representative samples of study population prevents compromises to external validity (Horan et al., 2015). The selection of study participants for inclusion involves the identification of individuals suited to address the overarching research question, and provide evidence a researcher may use to further the study (Sargeant, 2012).

Following the identification of a county government agency utilizing a BIS structure, using the LinkedIn® public database, I communicated with an authorized representative of the organization via email to assess interest in study participation (see Appendix A). The authorized representative of the government agency emailed all IS leaders and analysts to request participation (see Appendix B), and asked the interested employees to contact me directly. Through informed consent and disclosing the interview questions prior to the interview meeting, I established a working relationship with study participants. Andersen et al. (2012) argued subjects presented with the interview question prior to meeting were more confident in their responses. Permitting the interviewee a chance to review the interview questions prior to the meeting may orient participants to questions relating to personal knowledge (Mikecz, 2012). Moreover, granting research participants access to questions prior to an interview results in the disclosure of richer feedback (Englander, 2012). Revealing the interview questions to the study participants prior to the meeting may enhance the quality of the collected data.

The interview process creates a working relationship with and allows the interviewee to contribute personal insights and perspectives with limited inhibitions, compared to the restrictions imposed by closed-ended questions (Xu & Storr, 2012). Researchers and participants may begin the formation of an ethical working relationship by way of disclosures in the informed consent form with language expressing the desire to protect the individual's identity (Judkins-Cohn, Kielwasser-Withrow, Owen, & Ward, 2014). Doody and Noonan (2013) argued that establishing guidelines to provide participants with an understanding of complex question phrasing, and a potential for the discussion of sensitive topics prior to the interview, might aid the completeness of the respondent's answers.

Research Method and Design

Using a qualitative single case study method and design, I explored the best practices needed to implement BISs for effective resource management. Qualitative research allows the researcher to explore and interpret the experiences of the study participant (Parker, 2012). The qualitative researcher method was an appropriate selection to explore different sources, and collect the insights of the participant's professional experiences

Research Method

I chose a qualitative method to conduct this research. Qualitative researchers focus on finding meaning behind actions and behaviors, and serving the integral role of data interpreter (Sinkovics & Alfoldi, 2012). The qualitative research method is appropriate for researchers exploring complex management issues (Parker, 2012). Moreover, qualitative research is essential to uncovering the deeper meaning of a phenomenon that unfolds over time (Parker, 2012). The flexibility of the qualitative method allows the researcher to incorporate unexpected findings that arise during the research (Cope, 2014).

Qualitative researchers gain insight into an individual's experiences; the nature of the method allows the researcher to interpret experiences (Staller, 2010). Researchers are considered an instrument central to the study process in qualitative research (Frels & Onwuegbuzie, 2012). In addition, the use of a qualitative research approach establishes an environment to comprehend the human experience in a natural setting (Knudsen et al., 2012). Researchers use the qualitative methodology to increase the probability of understanding the meaning of micro-processes related to culture and context, associated with the collaboration and integration of sources (Teixeira, Jabbour, & Jabbour, 2012). I employed the qualitative method to understand the context of the study participant's personal experiences.

Researchers use a quantitative research method to test theories and hypotheses objectively by examining relationships between variables (Yilmaz, 2013). When using the quantitative research method, the goal of the researcher is to describe, predict, or control the occurrences or phenomena investigated (Gibson & Fedorenko, 2013). In quantitative research, an acquisition of knowledge can occur through the examination of numeric data that is analyzed using statistically based methods to determine relationships between variables (Gilstrap, 2013). Since I did not intend to test theories or a hypothesis, the quantitative research method was not suitable for this study.

Mixed method research combines qualitative and quantitative methods to collect, analyze, and merge data to provide a deeper understating of the research issue (Chilisa & Tsheko, 2014). In mixed method research the implementation of qualitative methodologies, increase the depth of understanding a phenomenon, while quantitative techniques allow researchers to test hypothesis and further comprehend predictors of effective implementation (Chilisa & Tsheko, 2014). Researchers use mixed-methods to combine participant experiences and statistical data to identify correlations between variables (Scammon et al., 2013). The purpose of the completed study did not include the exploration of statistical data in correlation with assumptions viewed through a theoretical lens, rendering a mixed method approach inappropriate.

Research Design

Petty at al. (2012) described five research design frameworks for a qualitative study: grounded theory, case study, phenomenology, ethnography, narrative, and methodologies. I chose a single case study design for this research. Researchers use the case study design to collect data from several different sources including observations, interviews, and archival documents (Yin, 2014). Using the single case study design, researchers can address how and why questions and focus on qualities, processes, and meanings in contrast to quantities, amounts, or frequencies (Kim, Price & Lau, 2014). The case study design is the dominant study approach in management research requiring qualitative analysis (Bizzi & Langley, 2012). The benefit of a case study design is the ability to explore and gain profound insights about a single complex entity (Petty et al., 2012). Researchers use an explanatory process in case studies to focus on the how and why questions, relating to the subject matter (Wynn & Williams, 2012). The case study design was appropriate for this study, because I collected data from multiple sources.

In grounded theory, the study participants represent a phenomenon, rather than a group of individuals experiencing a paradox (Adolph, Kruchten, & Hall, 2012). For the systematic exploration of data to identify theories (Parker, 2012) and explore social processes or actions researchers use a grounded theory design (Campbell et al., 2012).

Explorations of social processes or actions are beyond the scope of this doctoral study, for this reason ground theory was inappropriate for this study.

Researchers use the phenomenological design to focus on the meaning of the study subject's lived experiences with a relation to a particular phenomenon (Moustakas, 1994). The phenomenological design involves the study of a small population for a period with the purpose of identifying patterns and meaningful relationships (Petty et al., 2012). Using a phenomenological design, researchers collect data through cycles of questions and answers, with the intent to assign meaning to the experiences and derive expanded knowledge regarding a phenomenon (Tuohy et al., 2013). The phenomenological approach was not appropriate for this study, because I focused on the how and why of participants personal experiences, rather than assigning meaning to the lived experiences.

The ethnographic study design is useful to researchers exploring the behaviors of chosen cultural groups (Fetterman, 2010). Further, the ethnographic researcher explores the beliefs, and language of a society (Jansson & Nikolaidou, 2013). Ethnographers study cultural groups in a natural setting for a substantial period with the use of observation and interviews (Tong et al., 2012). Since I focused on the participant's experiences as opposed to my personal observations to describe behaviors or communication patterns, the ethnographic approach was not appropriate for this study.

The narrative design is a process of listening to participant's stories to identify the significance to the experiences and construct meaning applicable to a broader social context (Ison, Cusick, & Bye, 2014). Researchers use the narrative design to explore the meaning of study participant's detailed stories regarding their life experiences (Erlingsson & Brysiewicz, 2013). In narrative research, researchers gather creative and holistic person-centered stories from participants as the basis for data collection and analysis (Garud, Gehman, & Giuliani, 2014). Since detailed stories of life experiences did not add to the findings of this study, the narrative research approach was not appropriate for this study.

The interview process continued until interviewee responses were repetitive to ensure data saturation. Marshall et al. (2013) stated a sufficient study sample group provides data replication or redundancy. Moreover, Nakkeeran and Zodpey (2012) stated the objective in determining the correct qualitative sample size is subject to reflecting the purpose and aims of a study; with a focus placed on the quality of data, not quantity. Shuttleworth (2014) stated reaching data saturation occurs when the researcher hears the same information repeatedly without gaining new data.

Population and Sampling

The population for this study consisted of a purposeful sample of leaders and data analysts in an eastern U. S. county government that contributed to the function of the organizations BIS. The application of purposeful sampling prevents personal bias and generalized findings to a larger population, and provides the descriptive knowledge desired with the limitations of the study sample available (Petty et al., 2012). Researchers use purposive sampling to synthesize gained knowledge from different sources to make an explicit connection that did not previously exist (Suri, 2011). Purposive sampling is useful for conceptualizing results from a well-defined study population to identify regular patterns of behavior (Olsen, Orr, Bell, & Stuart, 2013).

The data collection process included interviews with four data analyst, and five IS leaders in an organization with specialized IS skills and expertise. Logan et al. (2013) defined stability in a study as achieving continuity between interviews, which may occur by interviewing as few as five subjects. Rowley (2012) conducted a series of semistructured comprehensive interviews with 5 to 25 participants, affording an integral understanding of the subject matter, by adding the respondent's perspective. O'Reilly and Parker (2013) argued a sample size is suitable when the information yield is sufficient for the researcher to answer the research question.

I reached data saturation by interviewing participants from a county government agency BIS until responses were repetitive. Logan et al. (2013) argued the optimal sample size for a study is determined by reaching saturation Nakkeeran and Zodpey (2012) stated the objective in determining the correct qualitative sample size is subject to reflecting the purpose and aims of a study; with a focus placed on the quality of data, not quantity. Further, a study sample group size is sufficient when the researcher reaches saturation; a point where new information is gathered (Marshall et al., 2013).

Requirements for participation included leaders tasked with the implementation of a county government BIS, and data analyst working within the boundary of that control. Participants maintained a position in a U.S. based county government and contributed to the function of the BIS. Participants completed a face-to-face interview for inclusion in the intended study. In qualitative studies, selecting participants capable of offering a diverse interpretation of the research question is beneficial (Yilmaz, 2013). The selection of potential study participants rests on the candidate's ability to address the research questions and provide an enhanced understanding of the topic (Sargeant, 2012). Knudsen et al. (2012) concluded a positive correlation exists between the quality of the participants' interview responses and a familiarity with the research question through personal circumstances.

In a private office at their county government agency, I conducted face-to-face interviews with participants. Interviews conducted in a face-to-face setting allow the researcher to gain more information by affording the participant confidentiality (Rowley, 2012). In a face-to-face environment with the interviewer, the participant is encouraged to share information in an atmosphere where the subject feels safe and comfortable, which may yield unexpected results applicable to a study (Jacob & Furgerson, 2012). Mikecz (2012) stated face-to-face interviews located in a place with minimal interruptions, allows an interviewer to develop trust and rapport, improving the quality of the responses to questions.

Ethical Research

Securing permission from a county government agency administrator and each participant via an emailed consent form confirmation occurred before the commencement of the intended research. The consent form contained detailed information regarding the study. Voluntary and informed consent are necessary for the ethical conduct of research (Horwitz et al., 2013). Participants could withdraw from the study at any time before the completion of the research by notifying me via email. Hadidi, Lindquist, Treat-Jacobson, and Swanson (2013) suggested that when conducting an ethical study, participants must have an opportunity to withdraw without penalty. The consent form included a statement advising no incentives existed for participation.

I conformed to all ethical and legal requirements including Walden University's Institutional Review Board (IRB) guidelines to ensure participants were free from harm or exploitation in the promotion of knowledge. Ethical research is the foundation for the production of excellence and significant to qualitative research (Sandelowski, 2014). According to Glerup and Horst (2014), all researchers must use methodologically sound and ethically just practices. When studying a community, precautions must exist to minimize risks to the individual subjects, as well as the group (Leitão, Falcão, & Maluf, 2015).

Sole access to all data and recordings stored on an external hard-drive, located in a fire rated safe for a period of 5 years, is limited to me. Following the designated period, a forensically validated data wiping process will render all data on the external hard-drive null. Yin (2014) stated the researcher must protect the privacy and confidentiality of the study participants to prevent inadvertent exposure to undesirable situations. After IRB approval, I commenced the study.

Omitting names and section/department positions in the agency protects the identity and privacy of all participants (Sandelowski, 2014). Research participants received an alphanumeric identifier to assure the confidentiality of respondent's identities and the integrity of the study. The analyst participant interviews received the letter *A* and a numeric for the sequence in the data collection process as an identifier (i.e. A1, A2, A3, and A4). The leader participant interviews received the letter *L* and a numeric for the sequence in the data collection process as an identifier (i.e. L1, L2, and L3). Confidentiality in research is desirable as a primary means of ensuring confidentiality, to mitigate potential risks or harm to participants (Damianakis & Woodford, 2012). Sandelowski (2014) argued that assigning research participants an alphanumeric representation provides confidentiality.

Data Collection

Instruments

Collection of data during a qualitative study is progressive, encompassing data gathered from multiple sources including interviews, document analysis, and observation (Hoon, 2013). As the primary data collector, I conducted face-to-face semistructured interviews (see Appendix C), and data triangulation using an archival document containing the operational model for the government agency IS. Five leaders and four data analysts from a county government agency BIS participated in the interview process. Interviews are the cornerstone of qualitative research, allowing the detailed exploration of a phenomenon (Serena Chiucchi, 2013). Further, semistructured interviews provide study participants with an opportunity to express experiences and perceptions in-depth without restricting answers (Elo et al., 2014). Standardized questions provide the control for a semistructured interview format, without inhibiting the exploration of topics introduced during the interview, to gain further insight into the study topic (Elo et al., 2014). Semistructured interviews using open-ended questions allow the measurement of each study participant's textual data, experiences, and the interpretation of relating personal perspectives (Nakkeeran & Zodpey, 2012).

Yin (2014) noted data triangulation requires the collection of information from multiple sources to develop converging points in the exploration of a research subject. The inclusion of an archival document in the study formed the data triangulation for this research. Researchers may use an archival document in data triangulation to balance the existence of stronger and weaker resources (Bizzi & Langley, 2012). Parker (2012) argued archival documents are a popular source of information collection in qualitative research, useful in the triangulation of primary data. Moreover, when a qualitative researcher expects a limited number of study participants, use of archival documents are encouraged to ensure the robust grounding of the researcher's interpretations (Ravasi & Canato, 2013). An advantage of using an archival document in qualitative research, as a key element for data triangulation is the corroboration of evidence gained from other sources (Yin, 2014).

An element of the face-to-face interviews involved me completing research notes subtly and recording them in a research journal. Note taking during interviews, aids in data organization, interpretation and to record discourse (gestures, body language, pauses, and verbal inflections) not evidenced in verbal transcripts, and adds to the richness of the collected data (Wahyuni, 2012). Interview notes ensure self-awareness during the process and enhance insights drawn from the data (Ward, Furber, Tierney, & Swallow, 2013). The collection of notes during an interview must remain subtle to avoid the potential of discouraging or disrupting the respondent's uninhibited expression of thought (Doody & Noonan, 2013).

Characteristics of qualitative research include a profusion of perspectives by the investigator, with safeguards in place to avoid bias and maintain validity and reliability (Sandelowski, 2014). Successful interviews require planning by the researcher to maintain the legitimacy and accuracy of the gathered data (Doody & Noonan, 2013). Wahyuni (2012) argued the research interview process is essential to the transformation of ideas from a spoken language into a written format for the management and organization of research data (Wahyuni, 2012). I used member checking to ensure the accuracy of transcripts. The use of member checking requires participants to read a summary of the recorded interview transcripts to verify accuracy and enhance credibility (Houghton et al., 2013). Further, member checking ensures the authenticity of the collected data (Onwuegbuzie & Byers, 2014). The use of member checking as a tool assisted me to maintain the legitimacy and accuracy of the interview instrument for study reliability and validity.

Data Collection Technique

Data collection began after IRB study approval number 07-01-15-0317262 from Walden University. Through email communication with an authorized representative of a county government agency utilizing a BIS, I gained permission to conduct the study and interview participants onsite. All potential BIS leaders and analysts received a request to participate from an authorized county representative (see Appendix B) via email. Interested employees contacted me directly. After determining participants met study criteria, I emailed an informed consent form (see Appendix C) that includes the study overview, withdrawal process, and data safeguard to all potential participants. Following the receipt of an email consent form reply of *'I Consent'* from the participant, I established a date and time for the face-to-face interview. In face-to-face interviews, the research may derive meaning to the responses through the vocalized answers and the participant's body language (Irvine, Drew, & Sainsbury, 2013). Vital to developing a rapport between the researcher and the interviewee for a successful face-to-face interview is gestures, handshakes, eye contact, and body language (Mikecz, 2012). In face-to-face interviews, the participant is immersed in the interview process and encouraged through personal participation to reflect on answers further (Rowley, 2012).

Participants received a copy of the interview questions (see Appendix C) through email correspondence before the scheduled interview. Englander (2012) determined that giving the research participants a chance to review the questions prior to the interview aids the process of disclosing richer descriptions during the interview meeting. Providing subjects with access to the questions before the interview permits the respondent to process difficult to answer queries and understand the material, allowing them time to ask for clarification for better final responses (Andersen et al., 2012). Mikecz (2012) emphasized revealing interview questions to the interviewee prior to the meeting orients participants to questions about their knowledge and serves as a basis of reference. Further, the disclosure of the interview questions prior to the meeting initiates a relationship with the participants and offers subjects an understanding of the research context for better responses (Mikecz, 2012).

I gathered information in a systematic manner from five BIS leaders and four data analyst via a semistructured interview format with opened-ended questions. The use of a semistructured interview permits the researcher to measure each participant's experiences and the relating of personal perspectives (Nakkeeran & Zodpey, 2012). Elo et al. (2014) argued that semistructured interviews provide a venue for study participant to express experiences and perceptions in-depth. Furthermore, Marion, Richardson, and Earnhardt (2014) conducted semistructured interviews with information systems decision makers at U.S. and Canadian organizations to evaluate industry practice discontinuance. The semistructured interview design afforded Marion et al. the ability to gather meaningful data and gain an understanding of relevant issues decisions makers encounter during the life cycle of an information system. The average length of each interview was approximately 50 minutes.

A digital handheld audio recording of all interviews occurred with the permission granted through the emailed consent form. In addition, I used a second digital handheld audio device as a backup to prevent the loss of interview data. Interview recordings aid in the analysis of data (Al-Yateem, 2012). Sorrell (2013) argued the recording of interviews aids in the coding and theme identification process. The use of a recording device provides a verbatim record of the interview and allows the interviewer to engage the respondent by avoiding distractions created by excessive note taking (Harvey, 2011).

Inherent advantages and disadvantages exist in data collection techniques. An advantage of the semistructured interview relates to the researcher's ability to control the research focus (Elo et al., 2014). The control a researcher possesses using a semistructured interview format offers an advantage in the data collection process, without inhibiting the participant (Elo et al., 2014). Semistructured interviews allow the interviewer to communicate as acquaintances rather than strangers, and offers commentary that may further the contextual accounts of the participant's experiences (Vogl, 2013). Moreover, semistructured interview questions promote flexibility in the communication encouraging depth and vitality in the gathered data (Doody & Noonan, 2013.

A disadvantage of utilizing the semistructured interview is the potential for a socially situated encounter (Doody & Noonan, 2013). A social encounter occurs when the interviewer fails to maintain a formal construct and permits the participa\nt to assume control of the research during the interview process (Doody & Noonan, 2013). Due to the conversational structure of a semistructured interview, the interviewee may fail to develop a trust with the researcher and prevent the discloser of valuable information (Andersen et al., 2012). Further, Yin (2014) stated in the semistructured interview reflexivity may cause the interviewee to offer answers they believe the researcher wants to hear.

All participants in the study received a summary of my interpretation of the interview transcript via email for member checking to affirm accuracy. Shields, Bruder, Taylor, and Angelo (2013) argued the use of member checking reduces the potential for bias. When study participants receive a summary of the recorded interview transcripts, they acknowledge and verify their own words, increasing the credibility of the interaction (Houghton et al., 2013). Permitting a respondent to review the transcript of the interview, contributes to the affirmation of study ethics, improves the quality of the research and empowers the interviewees (Wahyuni, 2012).

Data Organization Techniques

I identified participants with an alphanumeric title, associated with the interview sequence. An example of the identifier associated with the first analyst interview would appear as A1. In this study, the letter *L* represented BIS leaders and the letter *A* for data analysts. Assigning an alphanumeric representation ensures the confidentiality of the participants (Sandelowski, 2014). Researchers use unique participant identifiers to facilitate data management and cite information without unduly exposing the study subject’s identity (Haendel, Vasilevsky, & Wirz, 2012). The protection of a study participant's identity is an ethical issue and incumbent upon the researcher, as respondents may not fully comprehend the ramifications of involvement in research at the time of consent (Saunders, Kitzinger, & Kitzinger, 2014).

Throughout the data collection and organization process, I made interview notes in a research journal to assist with conformability relating to the reliability and validity of the study. Researchers use data logs to recognize and appropriately address the challenges associated with the interpretive flexibility of information (Sandelowski, 2011). Lin, Pang, and Chen (2013) argued a research journal is required to improve the conformability of a study. The minimization of ethical implications, the avoidance of potential bias, and increasing the trustworthiness of research material may occur when researchers utilize a journaling procedure (Greene, 2014).

After saving the interview transcripts in a Microsoft Word® format, I uploaded the information to NVivo® 10 to search for themes and patterns in the collected data. All study material and NVivo® 10 event logs will remain on an encrypted external hard-drive in a digital format, and placed in a fire rated safe only accessible to me for a period of 5 years. The design of NVivo® 10 software allows a researcher to sort unstructured data and structure subject matter (Ishak & Bakar, 2012). The rigor of a qualitative study increases when a researcher uses NVivo® to search for themes and patterns (Paulus, Woods, Atkins, & Macklin, 2015). Franzosi et al. (2013) stated researchers utilizing NVivo® 10 might establish code scheme hierarchies for information organizations and retrieval. In addition, researchers use the data tracking features of NVivo® 10 to establish an event log, and to complete the analysis of latent uploads associated with the study (2013). After which a forensically validated data wiping process will render all data on the external hard-drive null.

Data Analysis

The process of making sense of data collected through observation, interview, and other techniques is analysis (Yin, 2014). Using the qualitative research method, researchers may identify interrelationships between the production of information and the contextual meaning of collected data (Anderson, 2014). I utilized data triangulation for the analysis process using open-ended questions in the semistructured interviews of leaders tasked with the implementation of a county government BIS and data analyst tasked with the transformation of raw data into intelligence, and the review of the archival document containing the operational model for the government agency IS. Researchers use data triangulation to assist with confirming information and the thoroughness of data collection (Houghton et al., 2013). Collecting multiple data sources allows a researcher to corroborate the same fact or phenomenon (Yin, 2014). Moreover, data triangulation enriches the meaning of collected data (Hoon, 2013).

In addition, I reviewed the archival document containing the operational model for the government agency IS to complete data triangulation. The use of multiple data resources is required to provide a credible and precise case study (Houghton et al., 2013). Conducting data analytics simultaneously with other data collection methods allows the researcher to capture the reality encapsulated in the gathered information (Hoon, 2013).

Moreover, identification of relational dynamics during the research permits further exploration via follow-up interviews and the review of additional data sources to explore emerging themes (Yin, 2014).

Coding and Themes

The coding process involved an exploration of the interview question responses, and an archival document containing the operational model for the government agency IS. A coding process assists the researcher with the analysis and organization of collected information to provide meaning and value to the study (Sosnoski & Carlson, 2013). During the study process, researchers use text searches to aid in pattern identification processes and analysis, to determine if classifiable concepts received sufficient representation during the coding process (Knudsen et al., 2012). I used coding to confirm rigor and repeated instances in the study. Researchers use coding methods to assist with the confirmation of findings and prevent the misrepresentation of participant's views (Houghton et al., 2013).

I used the computer assisted qualitative data analysis software, NVivo® 10 and Microsoft Word® to complete node identification during the coding process to review the interview transcripts and archived data. Ishak and Bakar (2012) used Microsoft Word® and NVivo® 10 for coding and them identification. Coding interview data utilizing NVivo® allows a researcher to identify intersecting data points (Paulus et al., 2015) identified as nodes by software developers (Ishak & Bakar, 2012). The identification of nodes allows the researcher to provide contextual meaning (Paulus et al., 2015). Saving the collected data in a Microsoft Word® format minimized errors and formatting conflicts, during the import process for use in NVivo® 10 and aid in the qualitative coding process and data organization.

Designed for unstructured data, Ishak and Bakar (2012) utilized NVivo® 10 to reduce obstructions in the coding and analysis research processes. The use of NVivo® by researchers increases the rigor of a qualitative study (Paulus et al., 2015). The uses of computer software tools allow a researcher to conduct multiple types of analysis, increasing the probability of discovering underlying theories and relationships in data (Paulus et al., 2015). Classifying, sorting and arranging information aided the identification of themes and development of meaningful evidence for conclusions.

The thematic analysis process for identifying key themes requires the organization of datasets, classifying information, coding, and the interpretation of data (Vaismoradi, Turunen, & Bondas, 2013). Researchers may use a qualitative method to link key themes that emerge from research into a focused meaning, which occurs when data sets receive structure (Rowley, 2012). Moreover, Cameron, Naglie, Silver, and Gignac (2013) noted that using a conceptual framework to guide data collection and analysis in their qualitative research resulted in the emergence of key themes. I completed a literature review to add to the richness of the conceptual framework. Completing a literature review adds to the conceptual framework and development of key themes (Joo, McLean, & Yang, 2013).

Reliability and Validity

Reliability is essential to ensuring the accuracy and value of research data (Morse, 2015). Research validity is a product of reducing internal and external threats through process checks (Frels & Onwuegbuzie, 2012). In qualitative research, a researcher must incorporate dependability, credibility, transferability, and conformability in the study process to ensure rigor (Houghton et al., 2013). Researchers producing a reliable study may provide generalized results for a target population (Knudson, 2012).

Researchers ensure dependability by accounting for all changes in study conditions and any adjustments in the research design required for the enhancement of contextual understanding (Venkatesh, Brown, & Bala, 2013). Using member checking for data interpretation I ensured dependability of the research. Lotfi et al. (2013) determined member checking reduced researcher bias and increased the dependability of the research. Researchers use the member checking process to minimize the misinterpretations of interview responses, and to empower participants through an active involvement in the study (Perkins, Columna, Lieberman, & Bailey, 2013). Furthermore, in a study involving government employees, Walker and East (2014) used member checking to ensure the accurate portrayal of the participant’s perspective.

Credibility in qualitative research refers to an accurate representation through description or interpretation of the study participant’s experiences (Tong, Chapman, Israni, Gordon, & Craig, 2013). I triangulated semistructured interviews and an archival document containing the strategic operational plan for the government agency IS to explore best practices required to utilize BISs. Hoon (2013) argued the use of triangulation enriches the meaning of collected data. Triangulation ensures the corroboration of archival data, and interview responses are representative of the participant’s research topic understanding. Sandelowski (2014) cautioned the triangulation method is potentially time consuming and requires appropriate planning and organization. Furthermore, credibility occurs when several pieces of information point to the same assertion or proposition (Cope, 2014).

Using thick descriptions of the research processes, I provided readers with adequate information to determine if results of the study are comparable to other contexts. The transferability of findings to a second setting requires thick descriptions for readers to make judgments regarding the application of the information to their situation (Seale, 1999). Thick descriptions are not synonymous with long detailed characterization or explanations. Further, Seale noted the term thick descriptions, implies the need to provide a clear level of meaning for information. The transferability of study results increase when a research thoroughly describes the research context and the assumptions central to study (Denzin, Lincoln, & Giardina, 2006). Pedrosa, Näslund and Jasmand (2012) stated transferability refers to the applicability of research conclusions to the situation of other researchers, allowing them to form inferences.

Conformability is only present after credibility, transferability, and dependability are established and the evidence and results of a study are reproducible by another researcher (Cope, 2014). I implemented auditable processes for recording procedures, information collection, report analysis, and data interpretations. Morse (2015) argued, assuring rigor in research requires the use of an audit or decision trail documenting all decisions and interpretations made by the researcher. Employing a study audit trail readers may examine the processes applied by the researcher to produce the result, inclusive of accurate and recognizable descriptions (Houghton et al., 2013). Street and Ward (2012) examined the internal validity of case study research and stated the ability to overcome threats requires auditing results and accounting for alternative explanations.

Reaching data saturation, I ensured the trustworthiness of this study. Elo et al. (2014) stated developing a strategy for qualitative research must include data saturation to ensure reliability and validity of the study. Data saturation by continuing the interview process until no new information in gained from interviewee responses. A common guiding principle for data saturation is researchers must collect a volume of information sufficient to capture a full range of experiences without accumulating continually repetitious data (O'Reilly & Parker, 2013). Researchers reach data saturation to ensure enough the collected information accounts for all aspects of a phenomenon and provides the reader with a comprehensive source of data with minimum dross (Knudsen, 2012). Systematic and organized researchers include the analogous criteria for qualitative research to enhance the trustworthiness of their study (Elo et al., 2014).

Transition and Summary

Section 2 was a review of the chosen research method and design, including the data collection processes, analysis, instruments, techniques, and reliability and validation assurance practices. Section 3 includes the documentation of findings and results to the application of professional practice. Additionally, implications of the study on social change, an offering of recommendations, and a reflection on the research process occur in Section 3.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this qualitative single case study was to explore best practices needed by data management leaders to utilize BIS for effective resource management. Five leaders and four data analysts tasked with conducting BIS related functions in an eastern U.S. county government participated in this study. I used interview responses and information collected from the government agency IS operational policies and a procedures manual (archival document) to address the research problem. The findings derived from a review of the research data included a focus on the need for explicit policies and procedures to augment organizational asset performance through design and maximize BIS effectiveness. A reoccurring subject in the data included the training employees as informed information gatherers to improve the collection of valuable data for processing by BIS leaders and analysts. With frequency, leaders and analysts stated that leading, integrating, and managing human capital dynamics influences BIS functionality. Leaders and analysts acknowledged the difference in data analysis models and the benefits of choosing the correct method to analyze information. Further, BIS leaders could develop procedures to prevent intentionally bias or prejudicial data analytics. IS leaders and analysts need to understand data flow engineering relevant to all aspects of the IC to maximize resources in a BIS environment (Phythian, 2013).

Presentation of the Findings

The central research question for this study was: *What best practices are needed by data management leaders to utilize business intelligence systems for effective resource management?* I utilized semistructured interviews with open-ended questions (see Appendix C), and the cooperating organization's IS operational policies and procedures manual (archival document) to collect data for this study. I analyzed the research data using NVivo® 10. The five themes that emerged included the need to establish (a) the need for comprehensive policies and procedures for creating operating standards, (b) data acquisition training, (c) human capital dynamics management for improved efficiency, (d) protocols for transforming raw information into knowledge, and (e) safeguards for preventing bias in data analysis.

Theme 1: Development of Policies and Procedures for the Creation of Operating Standards

A successful BIS requires proper planning and the establishment of a detailed infrastructure to institute a proficient IS (Marrin, 2012a). Gold et al. (2013) stated key factors in developing a reliable predictive model for data analysis, requires an analytic framework outlining existing iterative and fluid dynamics, while incorporating the input of new data. Hoppe (2013) argued that leadership designing an organizational infrastructure with excessive focus on formality and ceremony, instead of intelligence workers as knowledge activists, might negatively influence the job performance of subordinates. Moreover, synchronicity in purpose through corroboration, reflection and action of IS personnel establishes an enhanced working environment (Hoppe, 2013). One (9%) leader stated “Validation, validation, validation with communication. We're making sure everyone knows what good intelligence is and good intelligence is validating information that's analyzed and usable.” Seven (77%) members of the study population agreed that a defined IS framework was required to maximize resources. Three (75%) analysts associated the proper flow of information and accessibility as a necessity for success in converting raw information into actionable intelligence. Access to stored IS information in a timely manner is critical and achieved by selecting an appropriate data flow technological solution (Chen et al., 2012).

In alignment with the key factors argument established by Gold et al. (2013), three (75%) analysts and three (60%) leaders provided indicators that the proper selection of personnel supported by technology, policies and procedures for analyzing information are key factors in developing a reliable analytic structure. Six (67%) of the participants stated inefficiencies of database design in a BIS negatively influence an organizations information storage and retrieval functions. Harrison et al. (2015) argued leaders reduce IC vulnerabilities through the establishment of detailed BIS policies and procedures. IS leaders must cope with inherently unstable, adaptive, and complex frameworks, increasing the level of difficulty and demands of managing resources (Coyne, Bell, & Merrington, 2013). The production of actionable intelligence requires the existence of proper data collection, data analysis techniques, business IC, and decision support systems (Chen et al., 2012).

All nine (100%) participants noted a deficiency in the selection and use of technology for data analysis, storage, and retrieval. In reference to information processing, storage, and retrieval improvement, three (60%) leaders acknowledged the need to frequently assess and plan for data analytic IT instrument improvements. The expedited correct parsing of big data requires IT tools (Den Hengst & Staffeleu, 2012). An overarching concern shared by all (100%) participants was the negative influence deficient technologies could have on the development of actionable intelligence. Further, three (60%) leaders and three (75%) analysts identified that the selection of incorrect or ineffective IS procedures by personnel hindered the ability to obtain actionable intelligence. The same participants cited that the use of improper procedures by personnel creates additional stress on human capital. Three (75%) analysts and four (80%) leaders indicated that allocation of human capital to complete BIS activities, coupled with technology to aid the data analytic process, are critical to the management of resources. The identification of patterns and themes in data occurs with the selection of an appropriate technological solution applied in a favorable environment (Steden et al., 2013). Organizational leadership's selection of IT solutions must support BIS functions to capitalize on critical success factors (Sangar & Iahad, 2013).

Organizations must create an intelligence structure aligned with leadership's, implicit or explicit, IC strategic goals (Farrokhi & Laszlo, 2013). Six (67%) participants acknowledged the need for detailed policies and procedures, to provide a definitive BIS strategy, personnel expectations, training, and goals. One (20%) leader stated, "I think the policies and procedures are already in place. I think the best practices are making sure that you are following those policies and procedures." Commenting on the existence of policies, procedures and training, one (25%) analyst stated "my training when I came in was just about how to do my daily alerts…it's really kind of learn-as-you-go, and you kind of get the feel for things." In Table 1, I illustrate the frequency at which participants mentioned the need for explicit policies and procedures to establish operating standards.

Table 1

Development of Policies and Procedures for the Creation of Operating Standards (Frequency)

Participant	Interview questions	Total number of references
A1	3, 6, 8, 9	4
A2	1, 2, 3, 8, 9	6
A3	2, 4, 5, 7, 8	9
A4	3, 5, 8, 9	4
L1	1, 4, 8, 9	6
L2	4, 8, 9	3
L3	3, 6, 8, 9	4
L4	1, 6, 7, 8, 9	6
L5	1, 2, 3, 5, 6, 8	6

Archival document analysis. Regarding the managerial philosophy for BIS operations, three (60%) leaders specifically referenced the description of an intelligence-led decision-making model in the government agency IS operational policies and procedures (archival document) manual ("Intelligence-2-Action Operational Model and Methodology" [I2A], 2015). Four (80%) leaders described the purpose of using an IS, as a managerial business philosophy focused on the collection and analysis of information to facilitate objectives, aid decision-making strategies, and effective resource management to serve stakeholders. However, four (75%) of analysts noted that an absence of detailed policies and procedures related to specific job descriptions, task assignments, and leadership and data analyst BIS training, hinder the efficiency of BIS operations. Popovic et al. (2012) stated a failure by leadership to rely on strict operational guidelines governing BIS functions, results in system deficiencies and the possibility of errant data analysis and conclusions. An explicitly defined BIS infrastructure, detailing the vital elements of the strategic features associated with training and team composition reduces the possibility of system failures (Sangar & Iahad, 2013). Furthermore, an explicit IS infrastructure minimizes IC vulnerabilities during BIS implementation (Harrison et al., 2015).

Theme 2: Data Acquisition Training

Bärenfänger et al. (2014) stated improper data acquisition wastes resources and causes distractions or misdirection for decision makers. Three (75%) analysts and three (60%) of the leaders expressed a need for proper information collection. Three (75%) analyst stressed a need for improved information gatherer training for data acquisition tasks. Three (75%) analysts indicated they frequently question the validity and credibility of information gatherer's data. Recalling a particular field interview entry by an information gatherer, one (25%) analyst commented, “I don't even know if this is accurate or not.” According to Sangar and Iahad (2013), a correlation exists between the collection of information from suitable sources and the enrichment of data using an appropriate analysis method to provide actionable intelligence. Six (67%) of the participants cited that procedures established by leaders at the government agency encouraged the collection of useless or flawed data. Further, the same participants expressed that organizational leadership has created an environment encouraging volume over substantive data collection. As Ramakrishnan et al. (2012) argued, to meet strategic BIS goals organizational leadership must define data collection criteria based on the potential use of information. Moreover, mass information collection may cause failures in an IS (Wigan & Clarke, 2013). Leadership may improve resource management by establishing data provenance and prequalifying information value (Amara et al., 2012).

Rudas, Pap, and Fodor (2013) stated an IS is a dynamic information processing system used to combine data gathered from different sources into actionable intelligence. Six (67%) participants referenced a formalized information collection format identified as a field interview. Five (56%) cited that information collectors are required to complete field interviews regularly as a measure of job performance. Six (67%) members of the study population cited that field interviews are often incomplete, filled with errors, or lacked any discernible value for transformation into actionable intelligence. Moreover, three (33%) participants described the data gathering process as flawed, resulting in the mass collection of worthless or limited value information. Related to the principles guiding information collection, one (20%) leadership participant stated, “we're trying to determine on a daily basis what do we need people to grab. What information do we need to acquire and feed up the chain?” The information collection processes may define the purposefulness of complied data (Wigan & Clarke, 2013). In Table 2, I illustrate the frequency at which participants mentioned the significance of data acquisition training.

Table 2

Data Acquisition Training (Frequency)

Participant	Interview questions	Total number of references
A1	3	1
A2	1, 2, 3, 7, 8, 9, 10	8
A3	1, 3, 5, 6	5
A4	2, 9, 10	3
L1	4, 6, 8, 10	4
L2	1, 6	2
L3	1	1
L4	1, 3, 4, 9	4
L5	3, 10	2

Prepared individuals possess the ability to adapt in a fluid work environment (Aminoff et al., 2012). Leaders establishing a plan to educate subordinates are central to the concept of valuable information sharing (Nandita, 2013). In response to questions three and nine, two (40%) leaders and two (50%) analysts suggested that modifications to the database input process would assist information gatherers in prioritization of collected data; creating an information value assignment. In the organizational policies and procedures manual (archival document), leadership referenced the IS as the defining source of intelligence in their organization (I2A, 2015).

Archival document analysis. In the archival document organizational leaders stated intelligence is a product of analytical processes to cultivate who, what, when, where and how elements from diverse information repositories (I2A, 2015). Information in the organizational policies and procedures manual (archival document) served as confirmation of leadership's expressed assertion that a productive BIS results in the application of best practices' relating to enhanced data analytics usage to formulate knowledge (I2A, 2015). Moreover, as described in the organizational policies and procedures manual (archival document), knowledge forms the basis of intelligence to determine a root cause for actions that may endanger or compromise public safety (I2A, 2015). As conveyed in the archival document, the process of information collection through reports, intelligence submissions, and field interviews for data analysis is vital (I2A, 2015). Government agency leaders, via the organizational policies and procedures manual (archival document), asserted that a correlation exists between the use of organizational resources and actionable intelligence derived by data analysts identifying contraindicated activity trends (I2A, 2015). Organizational leadership, to meet operational goals, must establish data collection criteria and define the potential uses for information (Ramakrishnan et al., 2012).

Theme 3: Human Capital Dynamics Management for Improved Efficiency

Vital to resource management and the sustainability of an organization is leadership's ability to value human capital as a resource (Gurses & Kunday, 2014). The integration and alignment of human capital management requires communication, mutual respect, and resolve by leaders and subordinates to achieve mission goals and functional excellence (Chadwick, Super, & Kwon, 2015). Five (100%) leaders placed a profound value on human IS components and the complexity associated with the collection and analysis of data. Based on the responses, five (100%) leaders valued the contributions of the analysts to the BIS. Nine (100%) participants conveyed an appreciation for the role information gatherers (internal) and stakeholders (external) perform in the development of actionable intelligence. The ability of organizational leaders to acquire, develop, share, and effectively employ knowledge to achieve goals requires skilled human capital resources for data control proficiency (Nandita, 2013).

Four (45%) of the study population attributed the efficient and accurate transformation of raw information into knowledge to the skill level of human capital resources. Leaders capable of employing human capital and integrating system resources to unify policies and business processes for improved efficiency are integral to organizational success (Chadwick et al., 2015). One (25%) analyst)stated, “I'm utilized as kind of a data entry clerk, so I'm inputting all the information and then I'm turning around and analyzing all of the information and determining what's valid or not and I feel like those should be three different tasks.” Leaders accomplish aspects of human capital integration by reducing job assignment fragmentation and duplication (Chadwick et al., 2015). However, concerning the leadership to subordinate role, one (20%) leader stated, “I don't know that the leaders need a lot of training, they just need to trust their people at the bottom and realize that the people that are in the trenches know what they're doing, and trust them.” Maintaining the integrity of IS components requires leaders to perform repeated task analyses and assess the value of human capital to minimize inefficiencies (Gentry, 2014).

Five (56%) of the participants described data control issues related to information access difficulties and reverse information flow. Three (75%) analysts noted the development of prejudiced information, citing how the actions of information gatherers bypassing the IC and predetermining the value of data without sufficient analysis, negatively influences the reliability of BIS outcomes. Five (56%) participants commented that accessing and disseminating information is problematic, citing examples of data floods post-analysis as a cause for reduced efficiency. Jyothirmayee, Reddy, and Akbar (2014) argued the complexity of collecting, storing, analyzing, and understanding the value of information for decision-making is challenging during a data flood. Furthermore, four (80%) leaders commented that ongoing information access improvements are necessary to disseminate BIS data proficiently. Rasanen and Nyce (2013) argued leaders facilitate work practices related to processing and storing information through the choice of a technological solution. Further, leaders should monitor selected IT solutions beyond the design and implementation phases of BISs to moderate needs for improvement.

Seven (78%) of participants cited flaws in the government organizational information flow structure that adversely affected BIS leadership goals. Identified disruptions in IS were attributed to (a) improper information collection methods and strategies, (b) the inability to access information in a timely manner by analysts, (c) misappropriation of analytic resources, (d) reverse information flow, (e) presumptive outcome request for data analysis, and (f) an inability to assess the accuracy of the analytic and IS process. One (20%) leader participant commented: “You know, it's still a computer, they don't have the ability…the emotions humans do, in the sense that leaders still need to have that humanistic side.” Another (20%) leader expressed a similar perspective on the need for the human capital factor, stating “I think as far as the human aspect of it we're pretty well staffed, but we all sit here and spin our wheels and struggle trying to get the information out of the computer.” One (25%) analyst noted a flaw in the IT solution used to access reports and information stored in the database, citing the inability to retrieve data in a timely manner. In example, three (75%) analyst)indicated requests for analysis and the IT solutions frequently do not align, preventing a comprehensive search or cross-referencing of stored data. Seven (78%) of the study participants shared a positive outlook for the future of the government organization, stating that preservation of human capital factors in a BIS environment is not negotiable. In the archival document, government agency leadership expressed a desire to transform information into knowledge, useable by decision makers to develop strategies and for better service to stakeholders (I2A, 2015). Mason and Simmons (2014) argued stakeholders seek timely and transparent disclosure of plans or strategies relevant to their views and concerns, by decision makers. Assigning value to human capital may assist leaders with maximizing resources to transform information into actionable intelligence. In Table 3, I illustrate the frequency at which participants mentioned managing human capital dynamics for improved efficiency.

Table 3

Human Capital Dynamics Management for Improved Efficiency (Frequency)

Participant	Interview questions	Total number of references
A1	3, 9	2
A2	2, 3, 5, 7, 9	5
A3	2, 3, 4, 5, 6, 9	7
A4	1, 2, 8, 9, 10	8
L1	1, 2, 3, 6, 7, 8, 9	8
L2	2, 3, 4, 9	4
L3	1, 2, 3, 10	6
L4	1, 3, 4, 7, 8, 9, 10	8
L5	1, 2, 4, 5, 6, 8, 9, 10	9

Leaders striving to utilize a successful information system in a Big Data environment, must employ data and task matching, and espouse the principles of vertical and horizontal computation parallelisms (Tallon, 2013). Six (67%) study participants agreed that analysts must possess the ability to retrieve stored information in an efficient manner to produce actionable intelligence. Four (100%) analysts commented that the timely review of raw information for further analysis is difficult as the volume of collected data increases. Further, the direct retrieval of specific data is challenging when information gatherers produce incomplete or errant entries. Louridas and Ebert (2013) identified that a failure to implement an adaptable IS strategy, where personnel are capable of adjusting for considerable increases in data, will result in the loss of actionable intelligence.

Archival document analysis. A review of the government agency IS operational policies and procedures (archival document) manual indicated leaders consider the need to analyze diverse information as critical, before data constitutes *intelligence*. In the archival document, using policies and procedures, administrators described BIS best practices for strategic processing of raw information by data management leaders and analysts to vet, analyze, store and share actionable intelligence (I2A, 2015). Government organizations using BISs will only meet goals through the promotion of a structured information flow (Schnobrich-Davis, 2014). Three (75%) analysts and one (20%) leader cited instances of agency leaders, information gatherers, and IS users obviating policies written in the archival document regarding the submission, handling, and analysis of data (I2A, 2015). Further, the same participants indicated that breaches in policy are negative influences, inhibiting the cultivation of valuable information from big data in a BIS environment. When leaders lack knowledge regarding raw data transformation into actionable intelligence they impede IS infrastructure maturation and render ICs ineffective (Popovic et al., 2012). Harrison et al. (2015) cited threats to the integrity of

ICs consist of unidirectional communications, poorly regulated meta-data management, and inadequate data stores. Moreover, deficiencies in IS structures encourage problems related to the efficient exchange of information (Harrison et al., 2015).

Theme 4: Protocols for Transforming Raw Information into Knowledge

The proper structuring of a diverse IS group capable of using different analytic methodologies, influences the success of an IC and reduces the probability of flawed outcomes (Phythian, 2013). Referencing training and job assignment to facilitate organizational goals, an (25%) analyst stated the need to “have the right people in the right job and the right training.” Eight (89%) participants agreed that personnel selection is essential to BIS success and should not suffer a diminished value with the introduction of IT aids. However, three (75%) analysts disclosed that job performance is hindered by a lack of analyst training and leadership’s absence of formal education related to data analytics and familiarity with IS job requirements. The benefit of an education in information processing competencies strengthens an analyst’s ability to process larger volumes of information proficiently (Wu, 2013).

Chen et al. (2012), and Den Hengst and Staffeleu (2012) stated ICs are most efficient when organizational leaders create an environment with a centralized information strategy and the employ highly educated people sharing a similar vision. During the semistructured interviews six (67%) participants articulated a comprehensive understanding of the organizational IS service vision, construct and function. The selection of data collection techniques and analysis methodologies for analysts to produce actionable intelligence is essential to the accuracy of leader's decisions (Chen et al., 2012). Moreover, the decision-making environment created by organizational leaders moderates the success of BISs (Isık, Jones, & Sidorova, 2013).

Although six (67%) of the participants expressed the existence of a centralized organizational strategy, five (56%) participants cited data collection and analytic practices that impede success. Seven (78%) participant's responses contained specific IS terminology regarding the selection of efficient data analysis protocols aligned with question five: *What data analytic model(s) does your agency need to utilize an IS to identify patterns or themes in information?* In response, one (25%) analyst explained, "If we want to look at anything from workflow and efficiency, to our way to allocate time based on incidence or anything like that, we should be able to with statistical certainly to make those decisions." In contrast to the assertion made by three (75%) analysts that statistical analysis is the most accurate technique, seven (78%) of the participants described the use of CBR (experiential reasoning) as the dominant technique to analyze information in the BIS. Marling et al. (2014) described CBR as an extension of human rationale, where individuals apply learned experience problem solving (Marling, Montani, Bichindaritz, & Funk, 2014). Sun et al. (2014) emphasized that the use of CBR requires analysts to possess prior case knowledge to achieve accurate outcomes. Analysts lacking a sufficient knowledge base may misinterpret data or apply flawed reasoning, negatively effecting outcomes (Sun et al., 2014). Eight (89%) participants agreed that the selection of an appropriate data analytic method is critical to cultivating intelligence from raw data.

CBR practitioners employ human rationale based on learned experiences to assess new situations or solve problems (Marling et al., 2014). Chang et al. (2015) argued the continued engagement of human capital resources using CBR is essential to maintaining a connection between contextual information and operative knowledge in a BIS. However, relying on CBR solely may result in data analysis outcome errors related to flawed reasoning (Ahmed, Banaee, & Loutfi, 2013). Behzadian, et al. (2012) noted CBR is an appropriate choice for data analysis, resulting in superior levels of accuracy in environments with reoccurring themes.

In alignment with the argument posited by Bauer et al. (2013), that a universal methodology for analyzing all data types within an organization for use by DSS staff does not exist, study participants cited the need to employ different techniques to analyze data for leaders. Four (100%) analysts and three (75%) leaders referenced the broad application of spatiotemporal analysis as a BIS analytic process. Three (75%) analysts cited BIS personnel tasked with predictive analysis select the statistically based spatiotemporal analysis method. Achieving accurate data analysis outcomes must begin with the process of selecting a technique to complete spatiotemporal distribution approximation (Ashby & Bowers, 2013).

Ashby and Bowers (2013) argued that insufficient research exists to validate the broad use of spatiotemporal analysis, or to insure the corresponding data analytic technique is not unintentionally substituted or compromised. When analysts' conduct spatiotemporal analysis they must complete multiple steps to assess geographic space and time relationships to identify any possible themes or patterns (Without the accurate use of spatiotemporal analysis methods, the credibility of the analyst's conclusions is questionable and may result in unreliable data outcomes (). Three (34%) participants cited frequent breaches in spatiotemporal analysis best practices, resulting in a reduction of accurate data available to leaders for decision-making.

All (100%) analysts advocated the use of multiple analytic methodologies with a preference for a scientific, mathematically based design such as a multivariate-reasoning model. Furao et al. (2010) described multivariate reasoning as a method to integrate multiple decision-making methods to process complex data. In response to question seven, a cross section of three (75%) analysts and three (60%) leaders conveyed an understanding of multivariate analysis. Eight (89%) participants expressed that multivariate data analysis would enhance the credibility and reliability of IS output. Three (75%) members of the analyst group perceived value in multivariate training, further stating that analysts educated to use multiple analysis disciplines would combine or choose the most applicable methodology. One (25%) analyst participant commented: "We are pulling the information, reading it, putting things together here and there, but we're not doing the full analysis part of it. We're not turning that information into intelligence. A lot of time I think we're just regurgitating." Valuable BIS outcomes are a product of analysts conducting quantitative (scientific) analyses, combined with intuitive and experiential (art) analysis (Marrin, 2012b).

Archival document analysis. In the operational policies and procedures (archival document), organizational administrators described the transformation of raw information into knowledge as a collaborative managerial philosophy to facilitate objectives, decision–making strategies, and effective resource management (I2A, 2015). Reviews of the government agency IS operational policies and procedures (archival document) revealed organizational leaders use data analysis to (a) achieve objectives, (b) aid decision-making strategies, and (c) accomplish effective resource management (I2A, 2015).

In the archival document, organizational leaders acknowledge the existence of different variables related to data collection and analysis (I2A). Data analysts use multivariate reasoning, and statistical analysis techniques to analyze information derived from more than one variable (Joshi, 2012). Joshi (2012) argued the use of the multivariate technique is an appropriate method for analyzing data when situations or decisions involve more than a single variable. Furthermore, multivariate reasoning consists of exploitation and incremental knowledge advantages without the duplication of results (Joshi, 2012). Three (75%) of the analyst participants recommended the use of a multivariate data analysis model to support agency leaderships goals. Further, in the archival document, administrators directly stated the goal of data analysis is to provide decision makers within an overall strategic view of identifiable problems and provide predictive information for the tactical allocation of resources (I2A, 2015). In Table 4, I illustrate the frequency at which participants mentioned transforming raw information into knowledge.

Table 4

Protocols for Transforming Raw Information into Knowledge (Frequency)

Participant	Interview questions	Total number of references
A1	1, 2, 3, 5	4
A2	1, 5, 4, 8, 9, 10	7
A3	4, 5, 6, 8, 10	6
A4	6, 7, 9, 10	4
L1	7, 9	3
L2	5, 6, 7, 8	5
L3	6, 7	2
L4	2, 6, 7	4
L5	2, 3, 5, 6, 7, 10	7

Theme 5: Data Analysis Bias Prevention Safeguards

According to four (100%) analysts and five (100%) leaders, all leaders within the government agency create data analysis requests based on their personal experience and an understanding of required information to assess past decisions, and current or future planning needs. Bauer et al. (2013) stated that absent cognitive influence, leaders employ experiential and numeric reasoning to form decisions. Experiential factors, directly related to CBR practices, involve problem resolution knowledge gained from analyst's experiences (Marrin, 2012a). Furthermore, Serban, Vanschoren, Kietz, and Bernstein (2013) explained leaders unfamiliar with best practices, possessing minimal training, experience, or guidance evaluate information based on trial and error. Moreover, Marrin (2012a) argued that using IS leaders or decision makers to conduct quality control evaluations to assess the accuracy and thoroughness of intelligence analysis outcomes is problematic due to possible bias. If leaders do not apply best practices during an organizational performance evaluation, incorrect assessments may occur compromising the decision-making process (Marrin, 2012a).

Four (100%) members of the analyst group disclosed that decision-makers frequently request data analysis based on ego, politics, and/or personal agenda. Six (67%) participants recalled incidents where requests to complete data analytics contained bias elements. As explained by one (25%) data analyst, “I think a lot of the way that our process is developed is bureaucratically and politically based and is removed from science and the academic spectrum.” Furthermore, one (20%) leader stated, “Of course there's bias. The key is I think, really, you have to understand that you're going to get that. You're going to get some political assignments that just have to be done.” Regarding bias in data analysis, one (20%) leader participant commented, “I think we just have to be cognizant of the way that we ask for that data from the analyst.” Four (80%) leader’s expressed, precautions to prevent intentionally prejudiced data analysis requests exist within the organizational construct; however, the leaders acknowledged the unintentional injection of bias may still occur. Moreover, three (75%) analysts stated whether the biased requests for analyses are an intentional or unintentional obviation of policy, any predisposition in data analysis risks the credibility of the results. In Table 5, I illustrate the frequency at which participants mentioned a need for bias prevention in data analysis for decision-making.

Table 5

Data Analysis Bias Prevention Safeguards (Frequency)

Participant	Interview questions	Total number of references
A1	8, 10	2
A2	2, 7, 10	4
A3	2, 4, 6	3
A4	4, 9	3
L1	5, 9	2
L2	1, 3, 10	3
L3	4	1
L4	3, 4	3
L5	3, 10	2

Business leaders use a systems thinking philosophy to troubleshoot BIS issues, without the encumbrance of pressures experienced by decision makers (Skaržauskienė & Jonušauskas, 2013). Skaržauskienė and Jonušauskas (2013) argued that members of a large operation might explore how each individual element of the group influences the overall construct to gain a better understanding of their role by using a systems thinking approach. Relating to requests for BIS data analysis, one (25%) analyst stated, “Personal vendettas on certain people. I mean, I think it's worse for some people than others" Three (34%) participants noted BIS integrity issues attributed to requests indicating the need for reports depicting the positive outcome of specific projects or programs; substituting the requirement of analysis for data demonstrating success. Marrin (2012a) warned preconceived outcomes might create a decision-making bias that influences the evaluation of data.

Themes related to bias and IS training emerged during the review of the semistructured interview responses. Popovic et al. (2012) stated a failure by leadership to maintain strict operational guidelines for BIS functions, causes data analysis deficiencies, and the potential for misinterpreted outcomes. Carter et al. (2014) stated counterproductive formal policies, insufficient staffing, and misdirected training curricula may inhibit an organizational paradigm shift to intelligence-led initiatives and decision-making by leaders. Five (56%) participants noted when a requestor supplies specific information and a directive to find particular results within the furnished data, the quality of the conclusion is questionable. Untrustworthy information, bias analytic assumptions, and computation errors represent flawed analysis outcomes (Shull, 2013).
Unlike a consumer-based system, government BIS leaders service stakeholders without profit as the primary driver (Kim & Schachter, 2013).

Archival document analysis. Evans and Kebbell (2012) identified fiscal cuts and increased media attention as influencers causing government agencies to assess operations to improve efficiency, maximizing resources and adopt business philosophies aligned with developing and managing a brand image. In a malleable business environment and to meet stakeholder expectations executives may request that leaders change organizational plans and goals, and adapt BIS functions to optimize processes and resource usage (Geller, 2012). Six (67%) participants cited that data analysis obviation occurs due to biased requests, rendering the need for valid and credible data analytics null. One (20%) leader explained that bias in the BIS is unintentional and not the direct cause of intentional personal manipulation. Government agency leadership declared, in the IS operational policies and procedures (archival document) manual, that due to dynamic multi-tiered factors within government and private organizations, personnel charged with IS duties should provide administrators with information that facilitates resource acquisition and utilization. However, one (20%) leader expressed concerns about meeting the expectations outlined by administrators in the operational policies and procedures (archival document) manual due to fiscal limits (I2A, 2015), and stated, “one I think because we’re civilians we’re often seen as kind of second class citizens in the agency. And so, when the training dollars get spread out they get spread out to the analysts pretty thin.” Seven (78%) participants concurred, explaining budget limits, political and bureaucratic pressures influence government IS leadership. Six (67%) participants identified external influences related to budgetary concerns and internal pressures that caused bias data analytic outcomes.

Findings Aligned with the Cognitive-Experiential Self-Theory

Epstein (2014) developed the cognitive experiential self-theory to demonstrate a person's capacity to integrate preconscious, unconscious, and conscious faculties to process information. The failure of leadership to make correct decisions regarding best practices may lead to IS failures. Armstrong et al. (2012) argued that CEST as developed by Epstein, includes an explanation of psychodynamic and psychoanalysis concepts used by humans to solve problems. Data analysts use CEST to analyze large and complex data sets (Worrall, 2013). Akinci and Sadler-Smith (2013) advocated the application of CEST principles by organizational leaders to establish best practices for the utilization of BISs with effective resource management. Using BISs as a knowledge cultivation tool, supported by refined data as a driver for the decision support process, improves the efficiency and effectiveness of a project (Ellis, 2013).

Participant responses supported the conceptual framework for this study: CEST. Four (100%) analysts and five (100%) leaders indicated that successful employment of analytic-rational and intuitive-experiential processes is essential to BIS functionality and meeting stakeholder expectations. Epstein (2014) stated that the premise of CEST is that humans possess two fundamentally different methods, analytic-rational and intuitive-experiential, for processing information. Epstein referred to this methodology as the dual information-processing paradigm. The employment of a dual information-processing paradigm by leaders may reduce the potential for bias, while improving the accuracy, of a person's decision-making (Epstein, 2014). Eight participants (89%) stated BIS leaders and analysts employ a dual information processing paradigm. Findings are relative to CEST as described by Epstein (2014).

Six (67%) study participants acknowledged the accuracy of data analysis outcomes increased as analysts gain experience and commented that expedience in analyzing information is critical for developing actionable intelligence. Armstrong et al. (2012) stated an individual’s performance and experiential competence increases through associative learning experiences. Findings relate to Epstein’s (2014) description of the human experiential decision-making system as an intuitive process within the scope of consciousness. In the absence of intuitive experiential reasoning, individuals employ slower deliberate language based brain activity for rational system analytics (Epstein, 2014). Moreover, Epstein (2014) explained that through the application of CEST, an individual’s experiential system evolves, increasing the automatic non-verbal operations outside the scope of awareness. In congruence with Epstein’ s argument for a link between experience and intuition, Ward and King (2015) stated the type of information processing a person chooses for problem solving and decision making differ with the individual's personal choice to employ rational analysis or intuition outside scope of awareness.

The research findings and the significance of the study were consistent with Akinci and Sadler-Smith (2013) recommendations for a deliberate construct in data analysis to increase the probability of accurate conclusions. The ability of personnel to proficiently identify the value of information, and assimilate the data for transformation into intelligence is an indicator of leadership's ability to establish a substantive technological BIS infrastructure (Jamil, 2013). Five (56%) participants conveyed concerns relating to a lack of adaptation associated with BIS protocols by leadership, affecting the production of reliable, actionable intelligence. Bauer et al. (2013) cautioned that favoring one type of data at the exclusion of another might result in sub-optimal outcomes. Organizational leaders must establish a relevant BIS framework, promoting the use of cognitive and rationale analysis elements of CEST, for effective decision-making processes (Curtis & Lee, 2013).

Findings Aligned with Existing Literature

The findings in this study might assist practitioners, and address a gap in the literature regarding best practices needed by data management leaders to utilize BISs for effective resource management. Popovic et al (2014) stated that a gap in literature related to the strategic management of BISs, necessary to understand information behaviors and the value to strategic planning exists. Researchers have concluded that BISs are costly, resource intensive, and complex to establish; however, limited contextual studies provide the necessary information for planning and implementation (Yeoh & Popovič, 2016). Researchers have documented the benefits of BISs; however, sufficient studies do not exist measuring and assigning value to each element for better process or resource management (Massingham, 2014). Xu and Yeh (2012) argued that best practices used by leaders exemplify the most effective, acknowledged, universal, repeatable, and efficient methods to facilitate an expressed goal. Leaders using best practices comprehend organizational goals, promote a team atmosphere, and efficiently manage resources in BIS settings (Gurses & Kunday, 2014).

Rdiouat et al (2015) stated that limited literature exists regarding the ability of organizational leaders to create adaptable BISs, except in the manufacturing industry to meet organization goals. Five (56%) participants stated concerns among BIS personnel relating to data analysis quality due to leadership's failure to recognize and modify procedures for operational needs, negatively influences the production of reliable intelligence through resource misuse. Six (67%) participants indicated the development of a reliable analytic structure for BISs requires the proper selection of personnel, technological solutions, and policies and procedures for data analyses. Congruent to my findings, Knabke and Olbrich (2015) stated limited literature is available, with the exception of software vendor documentation, regarding the design of an analytic structure and the selection of technical solutions to support data analyses.

Sharma, Mithas and Kankanhalli (2015) argued that additional research is needed to define the influence of organizational investments in decision-making processes, resource allocation, and the value of data analytics. When the incorrect intelligence analysis assessment techniques occur, results may include errant conclusions weakening the decision-making process (Marrin, 2012a). Seven (78%) of the participants cited the potentiality of errant BIS results or compromised data analyses attributed to uncorrected flaws in organizational information flow. Four (75%) of the analysts described how deficiencies in a BIS infrastructure reduce data processing effectiveness and result in the inefficient management of resources. Organizational leaders should understand interrelated BIS functions and associated limitations to evaluate data processing effectiveness (Popovic et al., 2012). Furthermore, Bloom et al (2013) confirmed the presence of a correlation between the execution of best practices and higher productivity.

Applications to Professional Practice

The most significant contribution from the study findings may be the identification of the best practices to operate BISs for effective resource management in the private and government business sectors. Identifying best practices leaders need for effective management of resources is critical to achieving organizational success in BIS environments (Gurses & Kunday, 2014). Government agencies and private sector organization leaders may consider the findings from this qualitative case study for the selection of a proper data analytic strategy and the construction of effective BISs.

Emerged themes from the study included information related to training, policies, and procedures, and may assist organizational leaders to increase the reliability of BIS outcomes for decision-making and operational goals. Furthermore, organizational leaders may use the findings from this qualitative case study to establish an efficient BIS infrastructure supported by meaningful operational methodologies to prevent bias, errant outcomes and the misuse of resources. Marrin (2012a) argued that leaders should forward requests for analysis free of bias. Preconceived conclusions by decision-makers may result in decision-making bias, influencing data analysis (Marrin, 2012a). Wu (2013) argued that training in information processing competencies increase analyst’s data processing proficiency. Moreover, resource management relates to the development of intelligence, directed training, and leadership establishment of a culture conducive to quality data retrieval and collection (Carter et al., 2014). Organizational leaders applying best practice guidelines to BIS functions may provide the necessary infrastructure to decrease the occurrence of bias in data analytics, errant outcomes and the inefficient use of resources.

The value of information begins with the point of collection (Shull, 2013). Trained analysts possessing the data analysis skills to complete multivariate reasoning and employ CEST might increase the production of actionable intelligence, and produce an organized reference database. Educated information gatherers may reduce the collection and storage of valueless material improving efficient data analyses (Amara et al., 2012). Martínez et al. (2013) stated that by establishing a statistical model to create a visual representation for multivariate data, leaders might reduce bias during data analysis. The use of visual flowchart to indicate the appropriate path data travels, from point of collection to action, might help personnel in understanding the BIS infrastructure. Further, organizational leaders could use visual analytics to create an environment conducive for the collation of new information quickly (Andrienko & Andrienko, 2013). Shull (2013) stated untrustworthy information, bias analytic assumptions, and computation errors represent flawed analysis outcomes. Reducing bias in the analysis process could result in effective management of resources. All (100%) participants expressed a confidence in the ability to analyze data with the purpose of serving stakeholders, when proper training and expectations are present.

Implications for Social Change

Thompson et al. (2015) concluded public and private organization leaders use the pervasive innovation of technology related to the storage and analysis of information to make informed decisions better serving society. The results of this study may assist domestic and international government agency leaders to recognize the value of knowledge led initiatives via BISs, to improve public safety policies and adapt business practices to provide security services. Fitz, Hauer and Steinhoff (2015) stated data is an asset equal to currency or gold, and government agencies should leverage information to offset fiscal limits. Moreover, various public service agency administrators might utilize BIS functions, maximizing resource management to complete predictive analysis for improved budget accuracy, and serve society as a whole through proactive services designed to prevent crises. Carter and Phillips (2013) stated government agency leaders use BISs to develop actionable knowledge and share information relating to public safety in a proactive effort to mitigate risks to society. Government agency leaders could increase subject matter knowledge, and reduce errors related to the anticipation or preparation of public service strategies by utilizing IS processes (Gibbs et al., 2015). Further, the vast data resources available to government agencies provide an opportunity to increase capabilities and services through predictive analytics (Fitz et al., 2015). Fitz et al. (2015) argued that the implication for social change and economics globally, due to the influence of big data is enormous. The findings derived from this study indicated that employing best practices could affect the ability of analysts to produce actionable intelligence for increased public safety and risk mitigation. Discovering improved application processes to apply BIS best practices may allow government agency leaders to adapt business procedures for effective resource management to improve public safety policies and services. Moreover, by utilizing best practices government agency leaders might increase information management proficiency, transforming information into knowledge for the development of affective regulatory policies.

Recommendations for Action

The research findings yielded data that may assist BIS leaders with the identification of best practices needed by data management leaders to utilize BISs for effective resource management. Furthermore, the results of this study might assist organizational leaders to effectively implement policies and procedures for the proficient production of actionable intelligence and manage resources in a BIS environment. I recommend the following actions based on the study findings:

- Organizational leaders should develop a detailed infrastructure constructed of policies, procedures, and role definitions applicable to all members of the organization interacting with BIS components to improve efficiency.
- Organizational leaders should develop a training system to educate information gatherers, with a focus on the thorough collection and recording of usable data needed by analyst to produce actionable intelligence.

- Organizational leaders could assess competency levels based on each analyst's degree of skill and capability (i.e. Intelligence Analyst 1, Intelligence Analyst 2) for task assignment and supplement each level with professional development training.
- Organizational leaders could benefit from acquiring and utilizing BIS technologies specifically designed for big data storage, sorting, and retrieval of information by analysts for the efficient production of actionable intelligence.
- Organizational leaders could standardize the data analytic technique selection and decision-making methods associated with task assignment to achieve a proficient use of resources with rapid processing of large data volumes.
- Organizational leaders should understand what constitutes data analysis credibility and be diligent to prevent bias; including specific requests for analysis.

Formal and informal modes of communication may exist within organizational infrastructures to communicate or implement recommended solutions. Organizations utilize formal and informal communication media to improve collaboration and participation, internally and externally (Mergel, 2013). Further, organizations use in-service (internal) training to teach and improve employee's competency levels (Piwowar, Thiel, & Ophardt, 2013). Communicating recommendations and refinements to personnel tasked with BIS related job assignments, via internal organization publications, is one possible venue for the distribution of IS procedural changes to personnel when the information is not confidential or does not create a security risk. In-service training cycle instructors could educate information gatherers in the appropriate data collection techniques and requirements for improved task competency. However, modifications to BISs requiring organizational policy and procedure changes should include a formalized communication mode to ensure mandatory compliance. Study findings might apply broadly to all organizations utilizing BISs to increase efficiency and assist government agency leaders with public safety policy development. I will seek to disseminate my research findings through a variety of industry and academic journals focused on BISs.

Recommendations for Further Study

Study findings may contribute to existing and future research regarding best practices needed by IS leaders to utilize BISs for effective resource management and strategic goal planning. Leaders must integrate intelligence into all business processes, including BIS functions, to improve decision-making and fulfill stakeholder expectations (Popovic et al., 2012).

A limitation in this study was the small sample size as this qualitative case study included only a single government agency. Future researchers may include multiple government agency levels or businesses located in different regions of the United States. Subsequent research might include an examination of the relation between BIS leadership techniques and practices for data analytic methodology selection. Utilizing an epistemological design, researcher’s may explore existing paradigms related to analyst’s and leader's sources of intuitive knowledge and the influence on BIS personnel functionality at local, state, and federal government agencies. The focus solely on best practices aligned with effective resource management in a BIS environment was an additional limitation of the study. Further research could focus on BIS staff behaviors and leadership styles to assess the best practice skills needed by BIS leaders for effective resource management.

Researchers could focus on the effect of policies and procedures on BIS success in future studies. I identified, using the findings from this study, that leaders of the government agency should understand all aspects of the BIS system, and take an active role to prevent the obviation of organizational BIS policies and procedures. Further, by maintaining a working knowledge and active role in BIS, leaders may maximize performance and improve the credibility and accuracy of information analysis. Further studies examining the relationship between organization policies and procedures, trained collectors, data flow engineering, and proficient data analysis might decrease errant BIS outcomes. Moreover, additional any research associated with skilled information collection best practices may provide BIS leaders with the necessary results to improve data analysis efficiency and increase positive DSS performance.

Reflections

Reflecting on my experience within the DBA Doctoral Study process, I discovered leaders should evolve organizational policies and procedures through a review process that includes the practitioner perspective. In example, administrator's assumptions regarding effective data analysis methodologies may not coincide with the best practices needed by the analysts to perform their daily duties and utilize BIS resources efficiently. Intentional or unintentional biases, agendas, and budget constraints might influence the utilization of BIS at a government agency. Furthermore, study participants did convey the existence of an environment where human capital was valued and acknowledged. Correspondingly, participants perceived that without proper guidance and training human capital resources could diminish BIS value.

Using semistructured interviews with open-ended questions, I encouraged in-depth discussions with study participants, gaining substantial insight into their perspective regarding reliable data analysis and BIS functions. The study participants indicated, without the selection of the correct technology by BIS leaders and training for human capital resources to obtain quality information, an impediment to the production of actionable intelligence may occur. Information gained from the literature review and study participant interview responses denote a correlation exists between BIS information source selection, the efficiency of data flow, and the ability to provide credible information for DSS purposes.

Summary and Study Conclusions

The objective for this qualitative single case study was to explore the best practices needed by data management leaders to utilize BISs for effective resource management. Utilizing semistructured interviews with open-ended questions and an archival document, I collected and triangulated data to answer the research question. Five themes emerged from the methodological triangulation of nine interviews and the archival document included the need to establish (a) the need for comprehensive policies and procedures for creating operating standards, (b) data acquisition training, (c) human capital dynamics management for improved efficiency, (d) protocols for transforming raw information into knowledge, and (e) safeguards for preventing bias in data analysis..

Relating to effective resource management in BISs, multiple factors articulated by the study participants were congruent with the expressed intent of the government agency leadership chronicled in the archival document. Moreover, the themes identified in the research findings were consistent with information garnered from the literature review. In example, as stated by Marrin (2012a) and confirmed in the research findings, a successful BIS requires proper planning and the establishment of a detailed infrastructure to transform raw information into knowledge. Seven (77%) of the participants referenced the need to establish IS frameworks to maximize resource. Further, three (75%) of the analysts professed that dynamics related to information flow and access in an IS directly influence the ability to transform information into intelligence for use by decision-makers. A substantial association exists between the implementation of best practices and optimal productivity (Bloom et al., 2013).

Three (34%) participants conveyed concerns related to the mass collection of worthless or limited value information negatively influencing the integrity of the BIS. The existence of proper data collection, data analysis techniques, business IC, and decision support systems may define the ability to produce actionable intelligence in a

BIS environment (Chen et al., 2012). Leadership must establish an IS structure supporting the IC strategic organizational goals (Farrokhi & Laszlo, 2013). Leadership's ability to evaluate and recognize the value of human capital as a resource is critical to achieving sustainability (Gurses & Kunday, 2014). Moreover, the statements of 100% of the study participants supported Phythian's (2013) argument for a proper IS structure comprised of a diverse group capable of employing different analytic methodologies to achieve accurate data analysis. All (100%) participants expressed a confidence in the ability to analyze data with the purpose of serving stakeholders, when proper training and expectations are present.

A failure by leaders to employ best practices in in a BIS environment may result in errant conclusions regarding the accuracy of intelligence analysis techniques and compromised decision-making (Marrin, 2012a). My findings illustrate a need for leaders to understand all aspects of the BIS, inclusive of information collection, storage, retrieval, analysis, reporting, and use by DSS. Data management leaders tasked with utilizing BISs for effective resource management must develop and adhere to best practices aligned with the current literature and research.

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Appendix A: Organizational Approval to Conduct Research

Walden University

Exploring Best Practices to Implement a Business Intelligence System

{Organization Name}
{Organization Contact}

{Date}

Dear Authorizing Representative,

My name is John McHenry and I am a doctoral candidate at Walden University, working to complete my Doctor of Business Administration degree with a concentration in Information Systems Management. I am conducting a dissertation research study on the best practices needed by data management leaders to utilize business intelligence systems for effective resource management. My research will involve interviewing ***leaders tasked with utilizing a business intelligence system, data analyst tasked with transforming raw data into knowledge,*** *and* the review of an ***archival document assessing the function of current intelligence system practices.*** Your organization was identified as meeting the necessary criteria. Therefore, I am contacting you to determine the possibility of including employees from your organization in my study.

Upon your approval of the proposed study, I will email you a letter of introduction with a request to forward the invitation to participate to all intelligence system leaders and analysts on my behalf. If permissible, all employees will contact me directly to express interest and receive an informed consent form for participation. All interviews will occur in private (i.e. the participant's office, designated office) and be scheduled to prevent any disruption to their workday. The desired archival document would include a professional study assessing the function of the organization current intelligence system practices, policies and/or strategies. You may terminate this agreement to conduct research at any time by providing written notice thirty (30) days prior to the expected termination date.

After the study is finalized and approved by Walden University, a summary of findings will be provided for review. The names of the organization, study participants, and requested archival document will remain confidential. If you would be willing to allow me to conduct the study with this agency, per the description above, please sign below.

Sincerely,

John McHenry

Authorizing Representative
Signature:_________________________
Print Name:_______________________
Print Table:________________________

Appendix B: E-mail Introduction

Hello XXXXXX,

My name is John McHenry and I am a doctoral candidate at Walden University working to complete my Doctor of Business Administration degree. I am conducting a doctoral research study on what best practices are needed by data management leaders to utilize intelligence systems for effective resource management?

I believe that your participation and your knowledge of data management/analytics, and intelligence cycles will make an important contribution to the research and available literature. I am requesting your participation in face-to-face interview and only ask for about 45 minutes of your time.

If you agree to participate in the study, you will receive a summary of the findings, which will provide an opportunity to learn what other best practices methodologies other organizations use to create effective intelligence systems. Your confidentiality will be protected.

If you are willing to participate in the interview process, please contact me at XXX-XXX-XXXX or via email at John.McHenry@Waldenu.edu with any questions and to receive a consent form for review. The consent form contains additional information about the study. Following the receipt of an emailed consent form response of *'I Consent'*, I will contact you to arrange a time and date for the interview. I look forward to speaking with you soon.

Thank you,

John McHenry

Appendix C: Interview Protocol and Questions

Interview Protocol

A. Personal introduction to the participant.

B. Verify participant received interview questions via email, and answer any questions and/or participant concerns.

C. Confirm the participant knows all interviews are recorded for accuracy.

D. Turn on the digital recorders.

E. Thank participant for accepting the invitation to participate in the study.

F. Start interview with question #1; follow through to final question.

G. Complete interview and discuss member checking with participant.

H. Turn off the digital recorders.

I. Thank the interviewee for their participation in the study. Confirm the participant has contact information for follow up questions and concerns.

J. End protocol.

Interview Questions

1. What task analyses are necessary to utilize an intelligence system for effective resource management?
2. What skills and training do leaders need to utilize an intelligence system for resource management?

3. What principles can leaders espouse when utilizing an intelligence system to establish best practices to manage resources?
4. What are best practices that may assist leaders in effectively utilizing intelligence systems at government agencies?
5. What data analytic model(s) does your agency need to utilize an intelligence system to identify patterns or themes in information?
6. How do the data analytic model(s) used by your agency transform information into actionable intelligence?
7. What data analytic reasoning process(es) should leaders choose for the implementation of an intelligence system for the proficient use of resources?
8. What information technology requirements are essential for the successful implementation of an intelligence system?
9. What knowledge relating to data analysis technologies and methodologies do leaders need for the effective utilization of an intelligence system to proficiently employ resources?
10. What additional information can you add that would be valuable to this study?