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Perspectives of IR Professionals Regarding the Impact of Data Analytic Systems on Institutional Decision- Making.

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Dedication

This Dissertation is dedicated to my late Father and Grandmother, love you both always.

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Abstract

The capacity for data analytical decision-making is not always optimal in institutions of higher education (Hawkins & Bailey, 2020). Data analytic decision making for this study is defined as any decision utilized to improve the process or outcome for any function of higher educational administration (Nguyen et al., 2020) including but not limited to: state appropriated funding (e.g. Campbell, 2018) improving graduation rates (e.g Moscoso-Zea, Saa & Luján-Mora, 2019), teacher instruction (e.g. Cai & Zhu, 2015), or student success (e.g. Foster & Francis, 2020). Many IR professionals still face obstacles pertaining to their ability to both utilize data analytical software as well as share data analytical findings across their respective clientele units outside of institutional research to impact institutional decision-making (Lehman, 2017). The literature is lacking concerning how IR professionals experience and navigate these critical aspects of data analytical decision-making support in higher educational institutions.

The purpose of this study was to address the gap in the research by assessing the perspectives of IR professionals regarding their ability to utilize data analytic systems (e.g., analyzing, interpreting, sharing of data) to impact and strengthen institutional decision-making. The purpose of this study was also to understand how institutional culture (e.g., policies, operational processes, relevancy, conduciveness) influences the ability of IR professionals to utilize data analytic systems when sharing data findings or collaborating across their respective institutions to enhance institutional decision-making. Recommendations based on the study findings included stronger data governance for dashboards and data visualizations, expanding predictive analytics to enhance student success, and data literacy training with both utilizing

data analytics software and interpreting data findings according to the context of individual institutions.

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Chapter 1 Introduction

The objective of this study was to provide insight into the perspectives of professionals from institutional research (IR) regarding the impact of data analytic systems on institutional decision-making in higher education. However, the impact of data analytic decision-making was examined from a functional or procedural, rather than technical, perspective. To accomplish this objective this study was employ two corresponding theoretical perspectives. First, this study utilized Knowledge Management Theory to examine the perspectives of IR professionals concerning their level of ability with operating data analytic systems for institutional decision-making (Lehman, 2017). Second, this study also incorporated Organizational Culture Theory to understand the perspectives of IR professionals in relation to the influence of their institutional culture on the knowledge management of data analytic systems, particularly when sharing or collaborating with data findings with other departments across their respective institutions to enhance institutional decision-making (Lehman, 2017).

The following provides a detailed report for this dissertation study, including the problem statement, study purpose, literature review, methodology, study findings, discussion, and recommendations. Chapter one provides an overview of the study including how data analytics is utilized within institutional decision-making, issues with understaffed institutions, the role visual analytics with institutional decision-making, problem statement, purpose of the study, and study limitations. Chapter two presents a comprehensive review of the current research concerning the impact of data analytics on institutional decision-making in higher education. Next, chapter three summarizes all aspects of the study methods and methodology including the research questions, research design, methodology, participants and recruitment information, interview protocol development, study procedures and timeline, analysis procedures, trustworthiness, and researcher positionality. Chapter four gives an overview of the study findings including themes and related interview excerpts, overarching perspectives related to the theoretical framework, and responses to the research questions. Finally, chapter five discusses how the current literature compares to the study findings followed by offering recommendations based on those findings. The chapter will then conclude with some brief closing remarks.

Data Analytical Decision-Making in Higher Educational Institutions

Every year institutions of higher education face a growing demand for more effective decision-making through data analytics (Webber & Zeng, 2019). Data analytics contributes to virtually every aspect of decision-making in higher educational administration (Nguyen, Gardner, & Sheridan, 2020), from state appropriated funding (e.g. Campbell, 2018) to improving graduation rates (e.g Moscoso-Zea, Saa & Luján-Mora, 2019), teacher instruction (e.g. Cai & Zhu, 2015), and student success (e.g. Foster & Francis, 2020). Given the ever-increasing volume of data needed for theses analyses, it is not surprising that the demand for data analytic utilization is a growing priority for institutions. University-based institutional researchers are prudent then to utilize such vast amounts of data that could potentially influence and support a plethora of administrative needs for decision-making (Hawkins, & Bailey, 2020).

Any plans to utilize institutional data, however, are irrelevant if the environment is not conducive for its effective use (Gagliardi, Parnell, & Carpenter-Hubin, 2018). Costs, for example, are often cited by institutional executives as a barrier to conducting broad sweeping analytical projects (Chaurasia, Kodwani, Lachhwani, & Ketkar, 2018), often inhibiting the resources needed for the additional training or staffing needed for data analysis and interpretation (Parnell et. al, 2018). In addition, inter-departmental access to data and data findings is also challenging for some institutions due to restrictive governance policies which sometimes “silo” data within separate departments, rendering some stakeholders skeptical regarding the feasibility of data analytic initiatives (Power & Heavin, 2017). It is therefore imperative for institutional researchers, analysts, and decision-makers alike, to overcome these obstacles and properly utilize data analytics for identifying trends, providing insights, and predicting educational outcomes to make effective institutional decisions (Gagliardi, Parnell, & Carpenter-Hubin, 2018).

According to the findings of a nationwide survey, Parnell, et. al (2018) identified some possible solutions for institutions lacking the resources needed for improved data analytical strategies. Parnell suggested for example, that a small group of analysts and analytical mangers from various institutional departments, such as IR, IT, and student affairs, form “Evaluation Teams”. These cross-departmental teams could mitigate some of the previously mentioned concerns and help develop broad sweeping institutional policies, such as uniform data governance and procedural policies that enhance data collection, analysis, and implementation. Moreover, Parnell also recommended that IR professionals serve as data consultants by assisting with the data analysis in departments outside of institutional research.

Understaffed Institutions

Despite these alternative solutions, some institutions still experience a shortage of qualified analytic staff which can effectively support the use of data analytic findings (Parnell et.

al, 2018). In a survey of US colleges from Inside Higher Education from 2019, it was reported that only 16% of private university provosts and 19% public university provosts perceived that their universities utilized data to effectively inform decision-making (Jaschik, S. & Lederman, D., 2019). Such a lack of confidence in the analytical ability of institutions could in part be due to some IR professionals struggling with properly operating analytical software systems during the decision-making process, which was a common issue found with analytical professionals in other fields outside of higher education (Knippenberg, Dahlander, Haas, & George, 2015). Some of these analytical professionals for example, may become so perplexed by the sheer volume of data required for analysis they will create overly complicated or irrelevant data analyses and visualizations making the interpretation of the data difficult to comprehend and thus hindering decision-making for future initiatives (Seymore, 2019).

As a result, these analytical managers, and perhaps IR professionals as well, may over-rely on their analysts or data scientists to support their decision making to compensate for their lack of analytical or technical ability, particularly if they do not possess the quantitative skills necessary to adequately interpret statistical findings (Webber & Zeng, 2019). Perhaps this is the reason why training is such an often-cited need of IR decision-makers in higher education to fill their knowledge gap (Parnell et. al, 2018). Without additional skill development however, organizations such as those in higher educational institutions will remain confined to their traditional roles toward data analytics, in which analysts exclusively interpret and present findings, while IR decision-makers indiscriminately take analysts at face-value for their rendering of the data, thus making their decisions based solely on the interpretation of the analyst (Williams, 2016).

The Role of Visual Analytics with Institutional Decision-Making

Fortunately, visual analytic (VA) systems have the capacity to help mitigate this knowledge gap between decision-makers and analysts. User-friendly and interactive, VA systems can enable decision-makers such as IR professionals to be more involved with the decision-making process by participating more knowledgeably with both analyzing and interpreting data (Williams, 2016). In a recent study utilizing analytical decision-makers from various fields including higher education, Williams (2016) explored how VA systems impacted decision-making regarding both individual decision-makers as well as their overall organizations, be it companies, hospitals, firms, or institutions of higher education.

In contrast to his initial hypothesis, Williams found that analytical decision-makers perceived that VA systems positively impacted the decision-making process organizationally, rather than individually. Meaning that decision-making was not significantly impacted by VA systems for individual decision-makers and their respective departments, however, did impact the decision-making for their entire organization. In addition, individual decision-makers also perceived that their own increased data interaction further enhanced the overall organizational decision-making process as well. To follow-up on these unexpected findings, Williams suggested that further research should explore the potential mediating effects of VA systems on decision-making across organizations, namely sharing data between other decision-makers. Williams speculated that sharing data with multiple decision-makers across an organization would perhaps enhance the effect of VA systems on decision-making through increased collaboration.

Regardless of their willingness to share data, some institutions still lack the resources needed to develop the knowledge base of their IR decision makers to utilize data analytical tools (Parnell et al., 2018) such as VA systems, much less the absorptive capacity to collaborate between decision-makers across an organization (Williams, 2016). Moreover, the attitude of the organization, or "organizational culture" of an institution may not be conducive to sharing data for institutional decision-making (Lehman, 2017). For instance, some institutions may not see the relevancy or even condone the sharing of data for decision-making purposes due to outdated data governance policies (Hayhurst, 2019). In addition, the personal reservations of managerial staff can also cause some institutions to be hesitant with sharing data, fearing that others might possibly misuse the data or that certain performance or career disadvantages might be associated with sharing data in higher education (Wilms, Brenger, Lopez, & Rehwald, 2018). Still, it is vital for IR leadership and their institutional leaders to understand the benefit of employing data analytical tools such as VA systems during the decision-making process. Doing so would perhaps help institutions prioritize the utilization of VA systems and find ways for its implementation to positively impact decision-making.

Problem Statement and Study Purpose

While the contributions of data analytics to institutional decision-making have been positive, these strategies are not always utilized to their fullest potential due to the many challenges noted, especially from the perspective of the leadership role of IR professionals. Moreover, in comparison with 4-year institutions, 2-year institutions are under increasing pressure to improve student success outcomes to compete for state-appropriated funding (Chen, Li, & Baber, 2018), and struggle with providing technical training, potentially impeding the effective utilization of data analytic decision-making (Parnell et al, 2018). Furthermore, the research literature is non-existent when considering the perspectives of IR professionals from 2-year institutions regarding their own knowledge level with operating data analytical systems as it pertains to institutional decision-making. This dearth of literature has also not explored how analysts and administrators rectify their differing levels of knowledge when making decisions from their respective interpretations of analytical findings. Lastly, the perspectives of IR professionals concerning their institutional culture towards sharing data across an institution to impact decision-making is also not well understood.

Other research that addresses this topic differ from this study in that they are either outside the field of education (Ajayi, 2014; Seymore, 2019), examine only limited aspects of institutional decision-making such as financial analysis (Campbell, 2018), or include only a small subset of participants from the field of education in the overall sample (Williams, 2016). This study therefore intends to remove these gaps in the research by thematically analyzing the perspectives of IR professionals concerning two primary aspects of impact from data analytic systems on institutional decision-making: Knowledge Management (i.e. the perspectives of IR professionals pertaining to their level of ability when utilizing data analytic systems to impact institutional decision making, either operating, sharing data, or otherwise) and Organizational Culture, (i.e. the perspectives of IR professionals concerning the influence of the institutional culture on their ability to utilize data analytic systems when sharing data findings or collaborating on projects across their respective institutions to enhance institutional decision-making).

Conclusion

This chapter provided an overall summary for this study regarding IR professionals perspectives of the impact of data analytic systems on institutional decision-making. The occupational demand of data analytics for institutional decision-making, the problem of understaffed institutions, the role of visual analytics for institutional decision-making, problem statement, study purpose, as well as study limitations were discussed. The following chapter provides a comprehensive literature review pertaining to the utilization of data analytics in higher education. Chapter 3 presents the overall research design and methodology of this study.

Chapter 2 Literature Review

The following chapter provides a literature review of research related to the impact of data analytic systems on institutional decision-making in higher education. The literature review will begin by providing a general description, as well as the beneficial uses of data analytics with institutional decision-making. The next section of this literature review will examine the skepticism of some institutional administrators with respect to the effectiveness of academic analytics with decision-making. This section will also distinguish between data-driven and data-informed decision-making. Subsequently, this chapter will then examine the challenges to data utilization, sharing, and collaboration due to both the individual ability of IR professionals and from the influence of their institutional culture.

This literature review will also outline the unique solutions provided by visual analytics systems with respect to data utilization, sharing, and collaboration both individually and institutionally. Finally, this literature review will conclude by explaining how the perspectives of IR professionals regarding the impact data analytical systems on institutional decision-making will be interpreted through two, corresponding theoretical frameworks: Knowledge Management Theory, as it pertains to the perspectives of IR professionals concerning their ability with data utilization, sharing, and collaboration for institutional decision-making, and Organizational Culture Theory, how ultimately the knowledge management of IR professionals is influenced by their institutional culture.

Academic Analytics in Higher Education

Research that examines the impact of data analytics on institutional decision-making in higher education is generally referred to as academic analytics (Nguyen et al., 2020). Other types of data analytical research in higher education include learning analytics, which is primarily concerned with improving learning and instruction (Aldowah, Al-Samarraie, & Fauzy, 2019) and educational data mining, which is the process of developing new methods and techniques for exploring educational data for future academic or learning analytic studies (Dutt, Ismail, & Herawan, T., 2017). This study, however, will focus on the functional impact (rather than technical) of academic analytics on institutional decision-making, such as the business intelligence aspects of institutional management, or the process of uncovering academic trends at the institutional level of administration, such as retention and graduation rates, or decision-making strategy (Chaurasia, Kodwani, Lachhwani, & Ketkar, 2018).

Academic analytics supports institutional decision-making on many fronts (Santos, Rodriguez, & Pinto-Llorente, 2020). Academic analytics can provide important data to administrators from a specific set of key performance indicators (KPIs), such as funding and budgetary information, admissions and enrollment levels, facilities and resource needs, or faculty, staff, and student performance metrics (Spear, 2019). Administrators can then utilize these KPI's for long-term decision-making by setting institutional goals and objectives, planning strategy, measuring progress, and hiring appropriate support staff (Saygin, 2019). In the past, such metrics would otherwise be unavailable to administrators with more conventional educational systems (Nguyen et al., 2020).

The development of academic analytical systems has also provided a means to rapidly respond to the constantly changing demands of institutional needs (Marks, Al-Ali, & Rietsema, 2016; Nguyen, Gardner, & Sheridan, 2017). These systems can provide automated, real-time data tracking for such metrics as enrollment, faculty productivity, and student achievement

(Cai, Garnova, Filippova, & Glushkov, S., 2021), allowing institutions to make decisions in a relatively fast and timely manner (McNaughton, Rao, & Mansingh, G., 2017). For example, institutions may employ academic analytical systems to gather quick insights concerning how to resolve performance issues during the development of a specific course (Daniel, 2015; Nistor and Hernández-Garcíac, 2018). One way to expedite the communication between institutional stakeholders are through automated "early warning" alerts from such platforms as visualized interactive dashboards, which notify administrators, instructors, or staff in real-time regarding at-risk or underperforming students (Foster & Francis, 2020). Thus, if properly utilized, academic analytics can more adequately comprehend student needs, improve teaching, learning**,** and advising (Cai & Zhu, 2015).

Institutions also benefit financially from academic analytics, in which some researchers contend that business outcomes are more important to institutional decision-making than the educational data itself (Campbell, 2018). Most states have incorporated some aspect of performance-based funding which are dependent on student success metrics (Ward, & Ost, 2021). Academic analytical systems can thereby inform administrators of the on-going progress of overall student performance while simultaneously assisting them with reducing costs by predicting and avoiding financial risks at the administrative and institutional levels (Drake, & Walz, 2018). Consequently, academic analytics can be employed to maximize available resources, improve accountability, and the reputation of an institution (Wong, 2016).

Other researchers assert however, that the main impetus for institutions to incorporate academic analytics for decision-making is to provide evidence-based methods and techniques which are both reliable and valid to better inform institutional decision-making (Harrison &

Waller, 2017). A more trustworthy method of informing institutional decision-making will then enable administrators to have the efficacy needed to plan strategically and effectively during important decision-making processes and if needed, implement effective institutional policies and processes to improve student success (Moscoso-Zea, Saa & Luján-Mora, 2019). Hence, it is essential for higher education administrators to optimally utilize data analytics to acclimate to the future demands facing their respective institutions (Ferreira, & Andrade, 2016). Yet some administrators still question the ability of data analytics to inform effective decision-making (Webber & Zeng, 2019).

Data-Informed Decision Making

Administrator skepticism pertaining to the use of data analytics to make effective decisions perhaps stems, at least in part, from outdated policies that are data-driven, rather than data-informed (Honda, 2018). With the emergence of data analytics in the 1980's, data-driven decision-making (DDDM) became the norm as organizations sought to have decisions made solely from the algorithms and heuristics derived from data analysis (Zhang, Zhang, Wang, Guo, Zhong, Qu, & Li., 2019). While certainly appropriate in specific, routine situations, such as "early warning" mechanisms for underperforming students or financial issues with tuition payments, DDDM has nevertheless neglected cultural, organizational, and human elements that cannot be reflected in the data (Lepri, Staiano, Sangokoya, Letouzé, & Oliver, 2017).

Eventually, many institutions included additional factors in their decision-making process and transitioned from DDDM to data-informed decision making (DIDM) (Webber & Zeng, 2019). DIDM not only analyzes the data but offers a contextual interpretation by joining the institutional decision-making process with organizational characteristics like student demographics, level of institutional funding, or the type of institution (Winkler & Fyffe, 2016). DIDM also incorporates the additional viewpoints from multiple departments of an institution into the decision-making process, as well as differing levels of staff, even those lacking analytic software skills like querying or programming (Swing & Ross, 2016). Utilizing so many additional outlooks, however, can potentially stall decision-making rendering the process ineffectual. Furthermore, producing an accurate interpretation of findings, especially with staff that do not normally analyze data, as well as garnering a consensus from multiple departments takes time and resources (Parnell et al, 2018).

Adding to this problem is that for some institutions data is still siloed in separate departments making it difficult for additional staff to access, particularly if data governance policies are restrictive (Parnell et al, 2018). For instance, one common issue with siloed data is the calculation of full-time equivalent hours (FTEs) for faculty. In some institutions, IR, human resources, and academic affairs all generate their own FTE numbers which could differ (Zheng, 2015). As a result of contrasting data from these seemingly identical variables, conducting student success studies can be daunting as it often involves IR, IT, student affairs, and academic affairs (Zhang et al., 2019).

It is no wonder then that some administrators of higher education are hesitant to initiate data analytic projects. In one study regarding the perspectives of administrators with data analytical decision-making indicated that a very small proportion of college presidents (12%) thought that data from IR was important for their successors (Gagliardi, Espinosa, Turk, & Taylor, 2017). Another study showed that only 16% of private, and 19% of public university provosts thought their institutions utilize data effectively to inform decision-making (Jaschik & Lederman, 2019). Such a lack of confidence in the decision-making effectiveness of data analytics can therefore cause uncertainty amongst administrators and instill a lack of buy-in from the institution with improvement initiatives like student success studies (Hawkins & Bailey, 2020). This is unfortunate as some administrators could miss opportunities to improve institutional outcomes like graduation, retention, and course performance (Foster & Francis, 2020).

Data Literacy

Relatedly, Tabesh, Mousavidin, and Hasani, (2019) have noted some prominent knowledge gaps between analytical mangers and their analysts from fields outside of education. These knowledge gaps, along with DDDM and siloed data, could be yet another possible reason for the reluctance of institutional administrators to implement data analytic initiatives. Knowledge gaps between staff can lead to improperly utilizing software and interpreting data analytical findings by applying them to the situational context of individual institutions. Because analysts are usually more qualified to work with quantitative data, analytical managers can become too dependent on them to operate the software, as well as analyze the data prior to making important organizational decisions. Likewise, analysts do not always possess the operational know-how to interpret data by applying it to a solution that is appropriate for their individual institution. As a result, a considerable knowledge gap can potentially emerge between analysts and analytical managers in which the decision-making process suffers from a lack of informed consensus. However, if IR professionals were to expand upon their traditional roles as solely the interpreter of the data by improving their data utilization skills, this knowledge gap could possibly be mitigated.

Thus, to make better data-informed decisions, analytical managers such as IR professionals need to make a stronger commitment to data literacy. Data Literacy involves both operating data-analytical software competently, such as conducting a data analysis, and understanding how to interpret data findings in accordance with the situational context of an individual institution (Hawking & Bailey, 2020). Moreover, IR professionals must also foster effective communication between staff and administration pertaining to the application of data findings with the institutional goals and initiatives from strategic planning (Tabesh et al., 2019; Lyytinen, & Grover, 2017). In some fields outside of education, analytical managers have been transitioning from their traditional roles of only an interpreter of data to being more competent with utilizing and interacting with data analytical systems (Williams, Lyytinen, & Boland, 2015). Even so, the data analytical research has yet to determine the impact of this role shift regarding the performance nor its long-term benefit in the field of higher education.

Data Sharing and Collaboration

In addition to the proper utilization of data, IR professionals will also have to share and collaborate with other departments to positively impact data analytical decision-making (Hawkins, & Bailey, 2020). One obvious way to enable data sharing and collaboration across an institution is through the dissemination of data (Mathies, 2019). One method of effectively disseminating data is by concurrently developing data-sharing mandates (Mathies, 2019) as well as creating online communities that share common data and analytical tools (Arellano, 2017). These combined methods ensure that analytical results will be accessed by the appropriate groups of an institution, and that higher-skilled staff can provide and manage the data for this network of information (Arellano, 2017). Having a strong governance policy working in tandem with greater data access also makes data sharing and collaboration more efficient while also avoiding a slow response from a central IT department (Arellano 2017).

Along with effective dissemination, Díaz, Rowshankish, and Saleh (2018) suggested that one possibility for institutions to improve data sharing and collaboration is to incorporate the already existing roles of institutional staff from other departments during prescribed scenarios that many institutions commonly face. These scenarios include but are not limited to: business – leading analytics transformation across the institution; data engineers - collecting, organizing, and analyzing data; data architects - providing data quality and uniformity of current and future data flow; workflow integrators – building interactive decision-support tools and implement solutions; visualization analysts - visualizing data, building reports and interactive dashboards; data scientists - developing statistical models and advanced algorithms to solve institutional or administrative problems; analytics translators – utilizing analytics to solve business problems; and delivery managers – integrating data analysis and interpretation to interface with end users. In this way, sharing responsibility across an institution will foster data sharing and collaboration and help establish a more data analytical organizational culture, which will positively impact institutional decision-making.

Ultimately, to improve data analytical competence with decision-making across an institution, administrators will either need to provide additional training and/or hire additional staff, as without competent staff, data dissemination and role expansion are irrelevant (Parnell et. al, 2018). However, some institutions lack the resources to provide these interventions.

Parnell offered some alternatives to traditional data sharing and collaboration strategies if in fact, training, additional staffing, or cost analysis studies are not an option due to lack of funding or resources. One method is to encourage IR professionals to act as consultants to other departments regarding collecting and interpreting data. Additionally, student affairs staff could likewise share student points of view and/or student engagement data with IR departments to supplement and even help explain performance metrics. A third alternative would be to establish a data governance "evaluation team", consisting of staff from multiple departments of the institution. An evaluation team could develop and expand current data governance policies such as creating a protocol for collecting, analyzing, and disseminating data. If financially possible, a chief data officer position could be created to oversee and coordinate evaluation teams as well as decision-support data projects that involve multiple departments across an institution.

Fittingly, the nationwide initiative "Achieving the Dream" (ATD) has been crucial with promoting data sharing and collaboration across the departments of 2-year institutions (Achieving the Dream, n.d.). Achieving the Dream is an initiative that assists faculty and staff from 2-year institutions with identifying and assisting academically struggling students from underserved populations through data and evidence-based decision-making. Some 2-year institutions have even utilized strategies from both Parnell et. al, (2018) and the Achieving the Dream initiative by creating cross-departmental evaluation teams or "data teams", whereby each participating department has at least one technical staff member. Notably, the IR departments often lead and collaborate with these data teams by training them with both the utilization data analytic software and with interpreting data findings according to the situational context of their institution.

These alternatives to outside training and staffing can help those institutions that lack funding establish an institutional culture more inclined to optimally utilize data analytics for decision-making (Parnell et. al, 2018). Even so, many IR professionals continue to struggle with operating data analytical systems more competently to make a difference with the institutional decision-making process, even despite a recent shift in their overall technical skill regarding data analysis and interpretation (Williams, Lyytinen, & Boland, 2015). Moreover, most analytical managers such as IR professionals will likely never match the technical expertise of data analysts and scientists (Lyytinen, & Grover, 2017). Fortunately, some analytical systems provide interactive and user-friendly interfaces through data visualization systems, enabling IR professionals to more competently participate in the process of analyzing and interpreting data for institutional decision-making (Campbell, 2018).

The Role Visual Analytic Systems in Higher Education

VA systems can effectively assist in analyzing data for analytical managers with less analytical, computational, or technical skills than their analyst counterparts (Williams, 2016). Institutions will often employ visualized dashboards as a way for administrative staff to track performance metrics and assist in decision-support projects (Mariani, 2016). In addition, dashboards are typically more interactive and user-friendly than other data analytical operational features (Campbell, 2018). IR professionals can directly access dashboards in real-time through a computer screen interface and manipulate charts and data, enabling them to not only contribute to the interpretation of the data but the analysis as well (Mariani, 2016).

Dashboards can also simplify data sharing and collaboration across an institution by allowing users simultaneous access online through a single institutional server from systems like SAS, Tableau, or PowerBI (Campbell, 2018). Utilizing a single server can securely and efficiently disseminate data across an institution from the IR or IT administrative departments (Mariani, 2016). A centralized server can also improve communication, avoid misunderstandings, and reduce the time commitment from the exchanges between users and IT regarding the multiple iterations of data (Maheshwary, 2015). Moreover, users across departments can interact on dashboards when testing hypotheses or assumptions and determine not only the reliability and validity of the data but decision-making impact as well, leading to better-informed interventions (Seymore, 2019). Furthermore, dashboards have control settings which regulate what stakeholders can see by restricting (or allowing) access only to data that is relevant to them. Consequently, with a safe and secure server, findings can be shared through the VA system with senior leadership (Lamba & Dubey, 2015). The accessibility of VA systems via dashboards can therefore potentially expedite the consensus of decisions across institutional departments concerning the data analytic projects (Mariani, 2016).

The problem is that organizational culture is frequently cited as an obstacle to the dissemination of information, often due to outdated and restrictive data governance policies (Lehman, 2017). When multiple institutional departments are needed to conduct decision-support studies however, VA systems can make data sharing and collaboration more secure by allowing departments to simultaneously access interactive dashboards or reports through one online, encrypted, password-protected, and centralized institutional server (Seymore, 2019).

Understanding this fact could potentially convince administrators to make data governance policies more effective (Mariani, 2016).

VA systems also more easily comply with data governance policies through automized editing mechanisms. To ensure accuracy when generating new visualizations, automated alerts inform the user during their analyses of potential errors and suggest possible solutions, such as adjusting variables or statistical weights (Williamson, 2016). In addition, inspection or evaluation procedures of data governance can be systemized and coded into a dashboard interface, which are automatically implemented once a visualization is uploaded, making compliance procedures automized as well (Ozga, 2014). By ensuring the accuracy (Williamson, 2016), compliance (Ozga, 2014), automation, and security of data, VA systems can circumvent potential administrative roadblocks from data governance that often hinder complex projects from integrating data sources (Mariani, 2016). VA systems can thus garner the buy-in needed when conducting decision-support projects from top-level senior leadership across institutional departments (Mariani, 2016).

To fully understand the impact of VA systems on organizational decision-making however, Williams (2016) conducted a mixed-methods study with a sample of analytical mangers from multiple fields including higher education. Williams was particularly interested with the concept of data interaction, which is the degree of interaction from individuals with specific system functions like data collection, analysis, and visualization. He hypothesized that data interaction, given its orientation toward the actions of individual participants, would only mediate the relationship between the quality of the VA system with decision-making on an individual, or departmental basis. In contrast, he did not expect data interaction to mediate nor have a significant relationship with organizational decision-making. Although interview responses during the initial phase of the study supported his hypothesis, structural equation modeling from an additional survey later in the study demonstrated that data interaction significantly mediated organizational decision-making, rather than individual or departmental decision-making.

Williams speculated that the impact on organizational decision-making was perhaps due to analytical managers simultaneously sharing and collaborating across their respective organizations while they individually interacted with the data. He further asserted that the organizational administration, or perhaps the organizational culture, could have also influenced analytical managers to share and collaborate while interacting with data. Williams therefore suggested that future studies would need to focus on the organizational impact of decision-making from VA systems, considering both the data interactions from individual analytical managers as well as possible influences from the organizational culture on data sharing and collaboration across an institution. Unfortunately, there are no studies in higher education examining the impact of organizational culture on data sharing and collaboration for decision-making. Although the Williams study, along with several other studies (Lamba & Dubey, 2015; Maheshwary, 2015; Seymore, 2019), proposed that data sharing and collaboration from VA systems as well as the corresponding organizational culture, could positively affect organizational decision-making.

Theoretical Frameworks

Knowledge Management Theory

Knowledge management is defined as the systematic process of establishing, compiling, and disseminating the intellectual capacity of people across an organization (Girard & Girard, 2015). The ultimate objective for IR professionals when implementing these processes is to accomplish institutional goals by maximizing the use of knowledge (Lehman, 2017), such as the utilization of data analytical findings for institutional decision-making. Knowledge management in higher education has demonstrated the ability to foster improved decision-making, cost reduction, and enhance the academic and administrative services by modifying unwritten, implicit knowledge into overt knowledge (Kidwell, Vander-Linde, & Johnson, 2000). Overt knowledge is often demonstrated in resources like institutional policies, procedure manuals, or documents such as mission, vision and value statements (Gao, Meng, & Clarke, 2008; Kidwell, Vander-Linde, & Johnson, 2000).

To optimize institutional decision making, IR professionals can therefore take more proactive approaches through their own knowledge management of data analytical systems (Williams, 2016). For example, if IR directors can improve upon their own ability to analyze or interpret data findings, they will contribute more directly with the knowledge management of the institutional decision-making process through an improved understanding of the data, while concurrently fostering a more informed decision-making process with their additional input (Hawkins, & Bailey, 2020). IR directors can also improve upon their knowledge management of data analytical systems by sharing findings with other departments during collaborative projects. This not only establishes a more conducive atmosphere for informed decision-making by adding more sources of input, but also begins the process of creating new knowledge within an organization by converting tacit knowledge into explicit knowledge such as policy changes (Steyn, 2004). Ultimately, for IR professionals to successfully expand upon their traditional roles there also needs to be a shift in the “institutional culture”, or attitude of the institution regarding the importance of data informed decision-making (Lehman, 2017).

Organizational Culture Theory

Changing the organizational culture is not an easy task as there are numerous obstacles to changing the entrenched mindset of an institution (Shein, 2010). According to Organizational Culture Theory, IR professionals will have to consider the various underlying assumptions, as well as the espoused beliefs and values of themselves as well as their institution (Shein, 2010). In addition, training will be crucial for both IR directors and other IR staff to better utilize data analytics for institutional decision-making (Parnell et al., 2018). Although, if analytical managers like IR professionals are successful with navigating the overall culture of an organization, as well as improving their competency with data analysis and interpretation, they will become more effective handling the constantly evolving needs of institutions by not only more efficiently identifying problems and planning solutions but also through the additional input from other people (Hawkins, & Bailey, 2020).

Sharing data findings across an institution to impact decision-making, however, greatly depends upon the attitude of the institution, or the “organizational culture” (McDermott & O’Dell, 2001). Organizational Culture Theory asserts that culture is a fixed set of values that a group of people share (Lehman, 2017). In many organizations, the culture is often apparent through standardized work paradigms (e.g. operational processes) or model assumptions that in the past were effective with solving problems and were thus impressed upon current employees as the normalized process of addressing current problems (Shein, 2010). Wherefore, organizational culture can greatly affect institutional decision-making through the expansion of knowledge and knowledge management via instruments, procedures, and actions (McDermott & O'Dell, 2001). One study for example, indicated that institutional culture was responsible for 90% of effective knowledge management (Leibowitz, 1999). Similarly, another study suggested that institutional culture was the second most critical success factor to knowledge management just behind leadership or management support (Wong & Aspinwall, 2004).

There are number of ways in which organizational culture interacts with knowledge management in higher education, however this study will focus primarily on those aspects related to sharing data findings from data analytical systems to impact institutional decision-making. One aspect of organizational culture that influences sharing data analytical findings for institutional decision-making are through the "espoused beliefs and values" of institutions. The espoused beliefs and values of an organization includes both the officially stated visions, missions, and goals of an organization as well as the ideals, principles, and person aspirations of individuals (McDermott & O'Dell, 2001; Schein, 2010). One notable example of this includes the established operational policies (McDermott & O'Dell, 2001; Schein, 2010) towards sharing data across institution, or data governance (Hopwood, 2008).

In the Higher Education Data Warehousing Forum's most recent survey of the top issues facing its members, over half (57%) of respondents chose data governance as their top issue (Gagliardi & Turk, 2017). This fact exemplifies one of the often-cited barriers from organizational culture on knowledge management which is the lack of resources for acquiring knowledge from current internal processes or technology (O'Dell & Grayson, 1998; Szulanski, 1993). In other words, the technology and data are available, but access is denied. Restrictive policies can potentially hinder the sharing of data for cross-departmental projects, and therefore it has been suggested that institutions should loosen or expand upon current data governance policies, such as developing a protocol for collecting and disseminating data (Parnell et. al, 2018).

Another aspect of organizational culture that influences knowledge management, or in the context of this study, sharing data analytical findings for institutional decision-making, are through the "underlying assumptions" of institutions. In the context of Organizational Culture Theory, underlying assumptions are defined as the unexpressed thoughts, feelings, and attitudes of the staff that can potentially influence work behavior or decision-making (Schein, 2010). The underlying assumptions of the organizational culture can hinder the sharing of data for institutional decision-making in several ways. For instance, administrative staff may simply assume a lack of value or existence of available data from senders or receivers alike and thus never attempt to share or receive data findings (Serban & Luan, 2002; Szulanski, 1993). At the same time, knowledge senders and receivers may assume a lack of cooperative relationships from staff outside of their department due to either the hierarchical structure of the organization or from simply the lack of a collaborative atmosphere conducive to data sharing (Serban & Luan, 2002; Szulanski, 1993). Lastly, staff may also assume a lack of positive incentives for sharing data with other departments due to organizational policies (Davenport & Prusak, 1998; O'Dell & Grayson, 1998; Szulanski, 1993).

Literature Summary

The previous chapter provided a literature review of research concerning the perspectives of IR professionals regarding the impact of data analytic systems on institutional decision-making in higher education. First, a general description of data analytics in higher education was given, including its more contemporary name “academic analytics”, followed by a summary of the benefits from utilizing data analytics for institutional decision-making. Next, the literature review explored the impact of data-informed decision-making in higher education by first distinguishing it from data-driven decision-making and then discussing how data utilization, sharing, and collaboration for decision-making initiatives are still a challenge for some IR professionals in terms of ability and institutional culture. Visual analytics was then examined as a possible solution to some of the challenges that IR professionals associate with institutional decision-making. This section of chapter however, stated that there was no research from the perspectives of IR professionals pertaining to their abilities to utilize, share, or collaborate with data, nor was there research the perspectives of their institutional culture effecting data visualization and analytical systems on institutional decision-making.

The chapter concluded with a review of two corresponding theoretical frameworks. First, this chapter explained how the tenets of Knowledge Management Theory would interpret the perspectives of IR professionals concerning their ability to utilize, share, or collaborate with findings from data analytical systems (Lehman, 2017). Secondly, principles from Organizational Culture Theory would interpret the perspectives of IR professionals regarding the influences of institutional culture on their knowledge management via data sharing and collaboration

(Lehman, 2017). The following chapter will outline the methods and methodology of this dissertation study.

Chapter 3 Methods

The following chapter will first review the problem statement, study purpose, and theoretical frameworks of the study. Subsequently, this chapter will then examine the methods of this study by describing the research questions, research design, methodology, participants and recruitment information, interview protocol development, study procedures and timeline, analysis procedures, trustworthiness, and conclude with the researcher positionality. This dissertation study utilized a basic (or generic) qualitative research design (Kahlke, 2014) and a thematic analytical methodology (Nowell et al., 2017) to address study research questions. Participant responses from one-on-one interviews were analyzed through the Clarke et al. (2019) six-phase thematic analytical process. The Interview protocol was designed by incorporating the corresponding frameworks of Knowledge Management Theory and Organizational Culture Theory as addressed in chapter 2 (Lehman, 2017). Informed consent, the interview protocol, and the participant recruitment email messages are presented in Appendix A, B, and C, respectively.

Theoretical Frameworks

Lehman (2017) asserts that knowledge management and organizational culture theory can offer guiding frameworks when addressing the use of institutional data or its interpretation. To support effective institutional decision-making, research administrators such as IR professionals must understand and participate more competently in their own knowledge management of data analytical software as well as both data analysis and interpretation. In addition, IR professionals must also address potential barriers to data sharing such as restrictive data governance polices and operational processes, as well as the underlying assumptions of the staff to better inform institutional decision-making. This study therefore sought to understand the perspectives of IR professionals concerning their ability to utilize data analytical software from the perspective of Knowledge Management Theory, as well as their perspectives regarding the influence of the institutional culture on their knowledge management via sharing data across an institution through the framework of Organizational Culture Theory.

The following research questions guided this study.

Research Questions

1. What are the perspectives of IR professionals regarding their ability to apply knowledge management (e.g., analyzing, interpreting, sharing, collaborating) when utilizing data analytic systems (e.g. visual analytic systems) to impact institutional decision-making?
2. How do IR professionals navigate institutional knowledge gaps (e.g., analytical vs. interpretive; technical vs. operational) when collaborating with other IR professionals by utilizing data analytic systems to impact institutional decision-making?
3. What institutional culture barriers (e.g., policies, operational processes, relevancy, conduciveness) do IR professionals encounter when sharing data or collaborating with other departments to enhance institutional decision-making?
4. How do IR professionals navigate institutional culture barriers (e.g., policies, operational processes, relevancy, conduciveness) when sharing data or collaborating with other departments to enhance institutional decision-making?

Method

This study applied qualitative methods to discover and understand the perspectives of IR professionals regarding the impact of data analytic systems on institutional decision-making within their existing institutional culture (Lehman, 2017). However, though these research questions encompass two corresponding theoretical frameworks previously, addressing them does not necessarily align with any common qualitative design or methodology (e.g., phenomenology, narrative, ethnography, grounded theory). Therefore, a basic qualitative research design was utilized for this study (Kahlke, 2014). Basic qualitative research designs typically draw on one or more accepted qualitative approaches and analyze the experiences of participants from a "bottom-up" or inductive process, utilizing codes, categories, and thematic analysis (Lim, 2011).

Accordingly, the qualitative approach of this study will take the form of a thematic analysis. In the past, it was argued that thematic analysis was not a qualitative methodology per se but merely an analytical technique (e.g. Ryan & Bernard, 2000). Yet, like basic qualitative research, thematic analysis was later justified as an appropriate methodological approach (Nowell et al., 2017). As a methodology process, it generally consists of recognizing, categorizing, describing, reporting, and analyzing themes found in qualitative data (Clarke et al., 2019). However, thematic analysis as an analytical process will be covered in more detail later in this chapter within the section titled analysis. Qualitative coding was based on the prevalence of participant responses, which in the context of this study involved the number of different participants (although not a set number) across the entire data set that articulated a given theme (Clarke et al., 2019).

Participants

IR professionals were utilized as the primary participant demographic in this study as they hold the prominent data management leadership position within higher education institutions, which is to establish data analytical processes to its fullest potential while also mitigating institutional risks (Hawkins, & Bailey, 2020; Gagliardi, Parnell, & Carpenter-Hubin, 2018). In addition, IR professionals from 2-year institutions were exclusively examined as they are typically under more pressure than their counterparts in 4-year institutions to improve student success outcomes to compete for state-appropriated funding (Chen, Li, & Baber, 2018). Furthermore, IR professionals from 2-year institutions typically belong to smaller departments than 4-year institutions and often have more training issues relating to data analytical decision-making (Parnell et. al., 2018). The term "IR professional" includes any staff working in IR departments such as Chief Data Officers (CDO's), Assistant Vice-Chancellors, Vice Presidents, Associate Vice Presidents, Executive Directors, and Directors, Associate Directors, Analysts, Data Scientists, other technical staff (Webber & Zheng, 2019). The job duties of these participants included utilizing one or more of the following job duties: data analytic systems for institutional decision- making; analyzing/interpreting/sharing/collaborating with data analytic findings for institutional decision-making; or participating on cross-departmental projects by utilizing data analytic systems for institutional decision-making.

This study employed purposive sampling (Dua, Bhaumik, Palinkas, & Hoagwood, 2015) and recruited participants using various IR related association listservs, such as the Association for Institutional Research, the American Association of Community Colleges, National Association of Assessment Directors, Directors of Institutional Effectiveness, Southern

Association for Institutional Research, individual IR professionals from personal contacts and network, as well as Tennessee Board of Regents and other similar organizations in surrounding states (e.g. Georgia, South Carolina, etc.). The sample size consisted of 12 participants, 11 of which were contracted through the Tennessee Board of Regents (TBR), while one participant was contacted from the Southeastern Association for Community College Research (SACCR).

Study participants consisted of 12 IR professionals (N = 12) from 2-year institutions which held various leadership positions in data management roles. Leadership positions held by the participants included Assistant Vice-Chancellor, Vice President, Associate Vice President, Executive Director, and Director. However, 8 participants held either the position "Executive Director" or "Director". To varying degrees each participant performed one or more of the following job duties: analyzing, interpreting, sharing, and/or collaborating on data analytic findings for institutional decision-making; either within their IR department and/or across institutional departments outside of IR. This study utilized participants almost entirely from the Tennessee Board of Regents (TBR) listserv. One additional participant was also included from the Southeastern Association for Community College Research (SACCR). Given that most study participants were from TBR, the other regional associations mentioned earlier in this chapter were also considered for recruitment. However, due to a lack of response over a month-long span it was decided to conclude the recruitment process according to IRB approved procedures.

The Tennessee Board of Regents is comprised of 40 institutions, 13 of which are community colleges, and is the largest system of public higher education in Tennessee. TBR is considered a Regents system which combines both the input from administration of the individual institutions as well as a centralized collaborative system education. Centralizing certain administrative aspects of these 40 institutions enables the Regents system to more efficiently implement policies to improve student outcomes in Tennessee, which are well below the national average. Furthermore, policy and other administrative changes are implemented by the TBR board staff, as well as conducting studies and providing centralized services.

Interview Protocol

A semi-structured interview protocol (Appendix B) was utilized to collect responses from IR professionals regarding their perspectives of the impact from data analytic systems on institutional decision-making. Interviews were conducted, audio and video recorded, as well as transcribed through online Zoom technology. This study was approved and complied with all appropriate IRB standards, ethics, and protocols pertaining to informed consent and protecting the identifying information of the participants. The protocol was created by modifying items from The Critical Success Factor Method Survey - A Foundation for Enterprise Security Management (Caralli, Stevens, Wilke, & Wilson, 2004). Lehman (2017) applied the primary concepts of critical success factors and enterprise security management from this survey to the corresponding frameworks of Knowledge Management Theory and Organizational Culture Theory. In the context of this study, critical success factors were defined as key performance areas that were crucial for managers such as IR professionals to know and consider (i.e. knowledge management, utilizing data analytical systems) when conducting operational activities and tasks that involved sharing data, or collaborating within and across institutional departments for institutional decision-making. Enterprise security management refers to the personnel, information, and technical assets an institution must possess to establish a security strategy (i.e. data governance) that can be implemented, measured, and revised as the business and operational environment changes over time (i.e. institutional culture). Table 2 below consists of the interview protocol and corresponding research questions.

Study Procedures and Timeline

Immediately following IRB approval in early May 2021, the interview protocol was reviewed to determine its relevance regarding the study topic of the impact of data-analytic decision-making in higher education. Subsequently, the Tennessee Board of Regents provided a listserv of IR administrators and staff from every public 2-year institution in Tennessee. This listserv was essential to the recruiting and data collection process, in which it provided 11 of the 12 participants utilized for this study. The recruiting, interviewing, and analysis occurred simultaneously beginning in mid-May and ending early June 2021. Lastly, the report was drafted mid to late June and the dissertation was defended in July 2021.

Analysis

A thematic analysis was conducted from the responses of IR professionals during one-on-one interviews (Clarke et al., 2019). All potential thematic content was analyzed inductively (Kahlke, 2014). In addition, utilizing a thematic analytical methodology enabled this study to analyze the data semantically as well as adhering to a realist/essentialist paradigm (Braun, Clarke, & Weate, 2016). All codes and themes were generated by utilizing MS Word and Excel software. Codes were identified by the prevalence of interview responses regarding certain themes across the entire dataset (Clarke et al., 2019). Interviews were both audio and video recorded as well as transcribed via Zoom technology.

The six phases of thematic analysis developed by Clarke et al. (2019) guided the analytical process of this study. The first phase involved the researcher familiarizing himself

Table 1. Interview Protocol and Corresponding Research Questions

Interview Protocol	Research Questions
1. As an IR professional, how would describe your daily work duties?	**RQ #1**
a. Do your work duties involve: analyzing data findings, interpreting data findings, sharing data findings with other departments, or collaborating on data projects with other departments?	**RQ #1**
b. Do your work duties involve using: institutional business metrics for funding/finances, key performance indicators (KPI's) for student success or curriculum/instruction?	**RQ #1**
2. What is the current data analytical (information) system your IR department uses for institutional decision-making?	**RQ #1**
a. In general, how would you describe the impact of your current data analytical system on institutional decision-making?	**RQ #1**
b. In general, how would you describe the data analytical system in terms of system quality? (e.g. ease-of use, interactive)	**RQ #1**
3. How would you describe the quality of communication with IR professionals that have differing roles from your own during the decision-making process?	**RQ #2**
a. Is your/their role mainly interpretive and functional? (i.e., implementing data analytic findings to improve institutional policies and processes)	**RQ #2**
b. Is your/their role mainly analytical and technical? (i.e., analyzing statistical findings; coding)	**RQ #2**
4. How would you describe the impact of the current data governance policies from your institution when sharing or collaborating on data analytic findings for cross-departmental projects?	**RQ #3**
a. Are there barriers to sharing findings across departments?	**RQ #3**
b. Are there barriers to collaborating on projects across departments?	**RQ #3**
5. How would you describe the general attitude of your institution when sharing and collaborating on data analytic findings for cross-departmental projects?	**RQ #3**
a. Does the general attitude of your administration present barriers to sharing/collaborating?	**RQ #3**
b. Does the general attitude of other departments outside of institutional research present barriers to sharing/collaborating?	**RQ #3**
6. How have you overcome these governance or attitudinal barriers while performing your duties as an IR professional?	**RQ #4**
a. When sharing data with other departments?	**RQ #4**
b. When collaborating on projects with other departments?	**RQ #4**
7. How do you utilize visual analytical systems for institutional decision-making?	**RQ #1 - #4**
a. How do you utilize visual analytics to interpret data analysis or when sharing data and collaborating with other departments for institutional decision-making? (e.g. dashboards, early-warning alerts, centralized server)	**RQ #1 & #2**
b. How do you utilize visual analytics to comply with data governance? (e.g. access settings, automized editing accuracy or compliance mechanisms)	**RQ #3 & #4**
8. Are there any other issues that have not been mentioned in the prior questions which effect you as an IR professional regarding the utilization of data analytical systems on institutional decision-making?	**RQ #1 - #4**

with the data. This included transcribing data and re-reading notations made during the interviews. In the second phase, initial codes were generated systematically from participant responses. During the third phase, themes were generated by collating each code to its appropriate theme. Subsequently, all themes were reviewed in the fourth phase by verifying that codes and themes were properly related from the transcribed and notated responses in phase one with the initial codes generated in phase two. Phase five consisted of defining and naming themes by refining the details of each theme from the "overall story" of the analysis. In the sixth and final phase, a report was generated consisting of prominent excerpts from participant responses as well as relating themes back to the research questions and theoretical frameworks. Table 3 below summarizes the overall analysis of the study, including the six-phases of the thematic analysis as well as additional steps to ensure the trustworthiness of the study. Steps to ensure trustworthiness are covered in more detail in the following section titled trustworthiness.

Trustworthiness

To establish trustworthiness for this study, several measures were utilized during the analysis of the qualitative data to provide consistency and accuracy of the findings (Creswell, 2014). First, the relevancy of the interview protocol was confirmed by the review of an IR professional from the Tennessee Board of Regents (Brod, Pohlman, & Waldman, 2014). Then, a university colleague experienced in qualitative research analysis evaluated the interpretation of participant responses as well as the accuracy of the item coding and thematic analysis (Lee, Ehlert, Kajfez, Faber, & Kennedy, 2017). The outcomes of these trustworthiness procedures are covered in Chapter 4 under the analyses and procedures section. The following table outlines the steps of the analysis and including trustworthiness procedures.

Researcher Positionality

The following is a summary of the researcher positionality. Positionality "reflects the position that the researcher has chosen to adopt within a given research study" (Savin-Baden & Major, 2013). As such, this section will examine any personal assumptions and biases which could adversely influence the trustworthiness of this study. I will also provide my educational background, work experience, and standing as a doctoral candidate. My educational background includes a Bachelor of Science degree in Biology from the University of Georgia, a Master of Science degree in Professional Counseling from Georgia State University, and my status as a doctoral candidate in the Evaluation, Statistics and Measurement program at the University of Tennessee – Knoxville. Having spent a considerable amount of time in academia has exposed me to the many overarching ideologies of higher educational institutions. One of these ideologies includes the assumption that the primary objective of institutions is to utilize its resources to improve administrative functions through institutional research, be it financial, instructional, or through student success. Working part-time in higher education has also afforded me the opportunity to participate in various projects related to institutional research as an outside researcher. Special consideration should be given therefore to represent the experiences of IR professionals from their perspectives rather than the perspective of the researcher. Steps for addressing these assumptions are addressed in the trustworthiness section of this chapter.

Table 2. Data Analysis Steps

Step	Task	Rationale
1	Interview Protocol Review and Revisions	Ensure protocol relevancy
2	Familiarizing the Data (Phase 1 of Thematic Analysis)	Transcribing and reading notations from participants responses.
3	Generating Primary Codes (Phase 2 of Thematic Analysis)	Code primary aspects of data systematically, compile data applicable to each specified code.
4	Identifying Potential Themes (Phase 3 of Thematic Analysis)	Compile codes into possible themes, collect all data applicable to each theme.
5	Reviewing Themes (Phase 4 of Thematic Analysis)	Verify relevance of coded excerpts of transcriptions and notations (phase 1) with initial coding (phase 2), generate 'map' of thematic analysis.
6	Defining and Naming Themes (Phase 5 of Thematic Analysis)	Revise aspects of each theme, and the overall analysis narrative, define and name each theme.
7	Generate Report (Phase 6 of Thematic Analysis)	Create prominent excerpts from individual participant responses of each theme. Interpret analysis in relation to research questions and theoretical frameworks. Outline implications and recommendations to IR professionals and future researchers.
8	Peer Review of Codes and Themes	Code and Thematic Accuracy

The basic terminology for this study includes institutional research (IR), data informed decision-making, data literacy, dashboard, predictive analytics, and data governance. The participant roles in IR for this study consist of IR professionals, IR administrators, IR executive Directors, and IR directors. Table 3 below defines the study terms while Table 4 describes the participant roles in IR for this study.

Study Limitations

The experiences of study participants working within the Tennessee Board of Regents system could potentially be vastly different from IR professionals of other state community college or 4-year institutional education systems. Overall, educational attainment in higher education for Tennessee is well below the national average (Statistical Atlas, n.d.). In addition, the TN Promise program provides two years of free tuition to all the public community colleges of TBR regardless of high school academic outcomes. Given that Tennessee is one of the leaders in performance-based funding from student success outcomes (Ward, & Ost, 2021), in addition to the emphasis of the state to increase its higher education attainment, as well as the possibility of drawing lower performing students due to the TN promise program, the demand for the expanded use of data analytics for decision-making purposes to improve student success could be higher than other state school systems. Conversely, Tennessee community colleges as a whole rank relatively high in comparison to many other community college systems across the nation in terms of overall effectiveness metrics (McCann, 2020), which may to some degree offset these demands. Nevertheless, it is difficult to speculate how these

Table 3. Study Terminology

Study Terms	**Definition**
Institutional Research	Research conducted at higher educational institutions to inform campus decision-making and planning in the following: admissions, financial aid, curriculum assessment, enrollment management, staffing, student success, student life, finance, facilities, athletics, and alumni relations.
Academic Analytics	Research that examines the impact of data analytics on institutional decision-making in higher education.
Data Informed Decision-Making	Analyzes the raw data of institutions but also considers contextual interpretations by joining the institutional decision-making process with organizational characteristics like student demographics, level of institutional funding, or the type of institution.
Data Literacy (or "Data Utilization")	Exhibiting the ability to both utilize data analytic software as well as interpret data findings. In the context of this study, Data Literacy is also more generically referred to as "Data Utilization".
Dashboard	A data visualization management tool that visually tracks, analyzes and displays key performance indicators (KPI) and other metrics to monitor the progress of an institution and assist in decision-support projects.
Predictive Analytics	Analyzes current and past institutional data to improve student outcomes through statistical techniques such as data mining, predictive modeling, statistical algorithms, and machine learning.
Data Governance	The process of managing the availability, usability, integrity and security of data in enterprise systems, such as data servers, storage, and associated software based on administrative data processes, standards, and policies.
Knowledge Management	The systematic process of establishing, compiling, and disseminating the intellectual capacity of people across an organization. (e.g. training, collaboration, data governance).
Organizational Culture Theory	The various underlying assumptions or espoused beliefs and values of an institution.
Institutional Culture Barriers	Barriers related to the organization culture which adversely impact knowledge management.

Table 4. Participant Roles in IR

Study Participants	Role in Institutional Research
IR Professionals	Staff working in IR departments such as Assistant Vice-Chancellors, Vice Presidents, Associate Vice Presidents, Executive Directors, and Directors.
IR Administrators	Institutional administrators such as Vice Presidents or Associate Vice Presidents that work with IR departments, specifically with IR directors before and during decision-making processes.
IR Executive Directors; IR Directors	Oversee IR department staff such as analysts, and report to administrators regarding data analytic findings as well as the interpretation of data findings within context of their institution.

dynamics effect the perspectives of the study participants in addition to how those perspectives would differ from either higher or lower performing community college or 4-year institutional systems.

Furthermore, the ability to utilize data analytical software or interpret data analytical findings could vary greatly between the IR participants of this study. As such, the study findings depended almost entirely on the ability levels of 12 IR professionals to properly utilize data analytical software and findings, potentially misrepresenting the ability of IR professionals from the overall population of Tennessee or nationwide. Efforts to mitigate these potential limitations were described in this chapter to certify that both methodological and researcher bias does not adversely influence study findings (Nowell, Norris, White, & Moules, 2017). Ultimately, future researchers should exercise caution however when applying any of the findings from this study to other institutions of higher education. Even so, it is the intention of this researcher to establish a framework of knowledge for future research regarding the impact of institutional decision-making from data analytics in higher education.

Conclusion

Chapter three described all aspects of the study methods and methodology, including research questions, research design, methodology, participants and recruitment information, interview protocol development, study procedures and timeline, analysis procedures, trustworthiness, and researcher positionality. The following chapter will cover the data findings of this study, including a thematic analysis of the data, how data findings correspond to Knowledge Management and Organizational Culture Theories, and responses to the research questions.

Chapter 4 Findings

The following chapter presents a detailed report of the findings for this study. This chapter begins by briefly reviewing the analysis procedures, followed by a review of the research questions and their relating themes to the data. This chapter will then summarize each theme, followed by a description of any correspondence found between the themes and both Knowledge Management and Organizational Culture theories (Lehman, 2017). The chapter will conclude by stating whether the findings of this study satisfactorily answered each research question.

Analyses and Procedures

Prior to analysis, the interview protocol was reviewed for its relevance pertaining to the study topic by an IR professional from TBR that was experienced in data analytical systems and institutional decision-making (Brod, Pohlman, & Waldman, 2014). Their determination concluded that the content of the interview protocol was relevant to the study topic in its entirety and therefore no revisions were needed. After the data collection procedures were completed as described in Chapter 3, an analysis of the data was initiated to develop emergent codes and thematic categorization in relation to the research questions of the study. The researcher then utilized MS Word to code the data and find any relevant quotations from the study participants, which were subsequently entered into an excel spreadsheet for further analysis to establish emergent themes and any potential connections between the themes and research questions. Coding of the participant responses was based on their prevalence regarding the number of different participants (although not a set number) that articulated a given theme across the entire data set (Clarke et al., 2019). Furthermore, all potential thematic content was analyzed inductively (Kahlke, 2014) and a thematic analytical methodology was employed to analyze the data semantically while also adhering to a realist/essentialist paradigm (Braun, Clarke, & Weate, 2016).

All codes and themes were analyzed utilizing the six phases of thematic analysis (Clarke et al., 2019). The first phase involved the researcher utilizing Zoom technology to audio and video record interviews, as well as transcribe the data and noting any initial impressions from the participants during the interviews. In the second phase, initial codes were generated by first transferring the content from the initial transcript to an MS Word document and systematically notating and highlighting participant responses. During the third phase, themes were generated by collating each code to its appropriate theme on an excel spreadsheet. All themes were then reviewed by the researcher in the fourth phase to verify that codes and themes were properly related from the content of the original transcription in phase one with the initial codes generated on the MS Word document in phase two. In addition, a university colleague experienced in emergent thematic coding and qualitative data evaluated the interpretation of the participant response codes, as well as the item coding and thematic accuracy (Lee, Ehlert, Kajfez, Faber, & Kennedy, 2017). Using an online software application, a random sampling of the interview data was conducted, providing approximately 10% of the total dataset for the colleague to review. All data was de-identified prior to the dissemination for review.

The reviewer determined the accuracy of the codes by reading specified passages from the participant interviews and matching them to their corresponding research questions. Codes related to the same research questions would in turn be combined to generate themes. The reviewer identified a total of 9 codes which did not match their corresponding research questions. The reason for these inaccuracies was not entirely clear and could simply be due to clerical error by the researcher.

Six of the codes identified by the reviewer however, matched other research questions and were included in the overall analysis. For example, when considering RQ2 regarding how to bridge knowledge gaps with other staff, one participant commented about how the student success rate leads to state appropriation, which in turn leads to a demand for more predictive analytics in community colleges. Although this statement was not a method to bridge knowledge gaps between department staff, it was related to RQ 3 and RQ4 concerning institutional culture barriers and solutions to those barriers, respectively. Relatedly, the difference in opinion from the participants concerning whether predictive analytics was a barrier or a solution as indicated in theme 5, as well as greater data access provided by dashboards in theme 4, is covered in more detail at the beginning of Chapter 5 in the Summary of Findings section.

In contrast, three additional codes, all pertaining to having or getting "experienced staff", did not answer any of the research questions and were therefore removed. Although at first glance the code "experienced staff" would appear to improve knowledge management ability (RQ1) or bridge knowledge gaps within departments (RQ2), these research questions only pertained to the knowledge management and navigation of knowledge gaps from the individual ability of the participant, and not from their colleagues per se. In addition, the code experienced staff is also not an institutional culture barrier (RQ3), at least not in terms of the underlying assumptions or espoused values and beliefs of an institution, which is established in the literature (Lehman, 2017). Nor is experienced staff a solution to institutional culture barriers (RQ4), as these barriers are usually lessened by implementing new policies and procedures from data governance or from the participant themselves through collaboration or training. Ultimately, even though experienced staff could be viewed as a missed theme not considered by the research questions, it was the general aim of this researcher to uncover how the participants perceived themselves (RQ1), perceived themselves in relation to their department (RQ2), and then how they perceived themselves in relation to other departments and their institution (RQ3 and RQ4).

After phase four of the thematic analysis was complete, phase five was implemented which consisted of defining and naming themes to clearly represent the "overall story" of the analysis. This phase included combining the initial theme of "Skepticism of Predictive Analytics" with part of another theme called "Additional Resource Needs" into one theme called "Ambivalence toward Utilizing Predictive Analytics in IR.". The remaining content from the former "Additional Resource Needs" theme was renamed to "Unmet training needs". Unmet training needs was later combined with another group of coding named "Met training needs", which ultimately led to the seventh and final theme: Training Needs Met or Unmet with Data Utilization. In the sixth and final phase, a report was generated consisting of numbered themes and prominent interview excerpts from the participant responses, followed by relating themes back to both the theoretical frameworks and research questions.

After conducting the data analysis and trustworthiness procedures, as well as finalizing all codes and themes, findings were then viewed from the lens of Knowledge Management and Organizational Culture theories, which provided the study a theoretical framework. Applying the analysis to these theories first involved relating the findings of knowledge management separately from organizational culture. In other words, participant responses relating to their ability to manage knowledge without any hindrances from institutional culture barriers were discussed. Subsequently, participant responses concerning how institutional culture barriers obstructed their ability to manage knowledge were examined (Lehman, 2017).

Research Questions and Corresponding Themes

The goal of this study was to answer the following four research questions:

- RQ1. What are the perspectives of IR professionals regarding their ability to apply knowledge management (e.g., analyzing, interpreting, sharing, collaborating) when utilizing data analytic systems (e.g. visual analytic systems) to impact institutional decision-making?
- RQ2. How do IR professionals navigate institutional knowledge gaps (e.g., analytical vs. interpretive; technical vs. operational) when collaborating with other IR professionals by utilizing data analytic systems to impact institutional decision-making?
- RQ3. What institutional culture barriers (e.g., policies, operational processes, relevancy, conduciveness) do IR professionals encounter when sharing data or collaborating with other departments to enhance institutional decision-making?
- RQ4. How do IR professionals navigate institutional culture barriers (e.g., policies, operational processes, relevancy, conduciveness) when sharing data or collaborating with other departments to enhance institutional decision-making?

Each research question corresponded with at least two primary themes from the data findings. All themes were uniquely defined according to the context of the study and were delineated by the various codes and excerpts collected from participant responses. Thus, each research question was also associated with the codes of each primary theme. The following table identifies each theme and its definition, the codes of each theme, and corresponding research questions.

Themes and Interview Excerpts

After considering each research question and contextualizing participant responses within both Knowledge Management and Organizational Culture theories (Lehman, 2017), seven overarching themes emerged from the analysis. The following paragraphs will provide an overview of each theme. Each thematic overview will restate the definition of the theme and its relation to the research questions. The codes for each theme will be briefly mentioned within each paragraph, followed by examples of matching excerpts stated by the study participants. Furthermore, each thematic overview will also consist of a table with matching codes and additional excerpts. Lastly, the theoretical frameworks of Knowledge Management and Organizational Culture will then be examined regarding their correspondence with each theme.

Theme 1. IR Director Confidence with Knowledge Management Ability

The first theme that emerged from the participant responses involved the confidence of IR directors to utilize knowledge management to impact institutional decision-making. Notably, IR director should not be confused with “IR administrator” or “IR professional”. Typically, an IR director is mid-level position in which they report to administration but supervise technical staff. However, this is not always the case, as some IR directors serve as both administrator and overseer of technical staff.

Table 5. Study Themes, Theme Definitions, Associated Codes and Research Questions.

Theme	Theme Definition	Codes	Research Questions
IR Director Confidence with Knowledge Management Ability	The confidence expressed by IR directors regarding their varied abilities to manage knowledge by utilizing data analytics for institutional decision-making.	• Utilizes Software for Data Analysis/Visualizations/Reporting • Informs Admin/Tech staff of Data Implications. • Collaborates Across Institutional Departments (e.g Achieving the Dream)	RQ1**.**, RQ2**.**
IR Professional Ability to Utilize Multiple Types of Data Analytic Systems for Institutional Decision-Making	Data-analytic software systems utilized by IR professionals to influence institutional decision-making	• Power BI • Banner • Argos • SQL Server • Excel • SPSS	RQ1.
Improved Student Success Achieved through Visualization	Improvements to student success including graduation, retention, or course performance due to decisions or initiatives resulting from data visualization.	• Student Success Initiatives • Administrative Understanding of Student Data • Identify At-Risk Students	RQ1.
Ambivalence towards Dashboards Providing Greater Access to Data	The mixed views expressed by participants regarding the level of data accessibility from analytical systems that are needed for institutional decision-making, including the level of access departments experience outside of institutional research such as faculty, and staff.	• Open Data Access with Minor Limitations • Data "Buy-In" from Faculty • Data Access Needs Limitations	RQ3. & RQ4.
Ambivalence towards the Effectiveness of Predictive Analytics in IR.	The mixed opinions expressed by participants regarding the potential effectiveness of using the various statistical techniques employed by predictive analytics to analyze current and past institutional data to improve student outcomes.	• Lack Of Feasibility • Lack Of Student Privacy • Lack Of Admin/Staff Understanding • Improves IR Department Function • Predicts Students Outcomes • Identify At-Risk Real-Time (Monitors & Tracks Performance)	RQ3., & RQ4.
Navigating Knowledge Gaps between IR Staff and Administration with Data Utilization	Any action taken by the IR directors to understand the more technical applications of data analysis used by the technical staff, and/or assisting the technical staff with understanding the administrative applications of the data analytical findings, resulting in more data-informed decision-making.	• Directors Understand Duties of Technical Staff Through Effective Communication. • Tech Staff/Directors Can Better Impact the Application of Data when Included/Updated regarding Administrative Meetings.	RQ1. & RQ2.
Training Needs Met or Unmet with Data Utilization	Implementing, not implementing, the action of teaching a person a particular skill such as analytical software utilization or the application of findings from analytical software.	• Unmet Argos Software Training • Unmet Administrative Skills Training • Met Power BI Training • Met Customized Administrative Application Training BI	RQ1., RQ2., RQ3., & RQ4.

This theme was defined by the confidence expressed by IR directors regarding their varied abilities to manage knowledge by utilizing data analytics for institutional decision-making. This theme was also related to RQ1 when considering the ability of the IR professional to manage knowledge by utilizing data analytic software systems for institutional decision-making. This theme also corresponded with RQ2 pertaining to navigating knowledge gaps when collaborating with other IR professionals by utilizing data analytic systems to impact institutional decision-making.

The first coded aspect of this theme was evidenced by how often IR directors personally utilized data analytical systems for analysis, visualizations, and reporting, and did not necessarily have to rely on their staff for technical needs. *"I am the administrative leader of our office, but I also do quite a bit of data analytics managing you know ad hoc reporting and so forth, and so on, I do have…two programmers in my office who deal directly with pulling data from our various data sources, but I also can do that as well, so i'm not always reliant on a programmer analyst but for the big projects, I do use utilize them as well."* (Participant #2).

Second, IR directors sometimes serve as the "liaison" between technical staff and administration and are often needed to explain the data analysis implications to both technical staff and administration. *"…I have the liaison role, and so, then I will consult with the Vice President, and the President about the (SACS) standards and all that…*". (Participant #11). In the same interview this participant also described how they advised technical staff: *"when… (the analyst) started here…we had to sometimes remind her to think about…put some thought into the analytics part because …I had to get her to think in terms of…the inner workings of the* *strategic planning process and…it took like two years, but it really takes that long and so there's a lot to it..."* (Participant #11).

Third, IR directors often also manage knowledge by leading data-informed collaboration initiatives across departments, especially since the advent of the "Achieving the Dream" initiative, which was created to address equity issues in community colleges across the nation. Some of the data-informed aspects of this initiative include establishing data processes to identify achievement gaps among student groups and using data for strategic planning to set measurable goals for student success outcomes. *"we do have like a data team (across departments), so we do have a team of like myself, as well as some of the Deans and some of like the registrar…academic affairs, student services, registrar… we have a group of people that can come together and if we have data issues or there's questions, we can come together and discuss it…so we can kind of all work together to come up with solutions".* (Participant #9). Table 6 below identifies each code of this theme and provides several corresponding excerpts from participants regarding IR director confidence with their knowledge management ability.

Theme 2. IR Professional Ability to Utilize Multiple Types of Data Analytic Systems

The second theme of this study pertained to the ability of IR professionals to utilize data analytic systems. Although this theme is similar to one aspect of the first theme concerning IR director confidence with their knowledge management ability to utilize data analytic software, it is differentiated from this aspect in two ways. First, the purpose of the second theme was to highlight the various types of data analytic software utilized by IR professionals regardless, whereas the first theme merely indicated that IR directors had confidence in their knowledge management ability to, in fact, operate data-analytic software in a general sense, without

Table 6. Theme 1. Codes and Interview Excerpts.

Codes	Interview Excerpts
Utilizes Software for Data Analysis/Visualizations/Reporting	"I am the administrative leader of our office, but I also do quite a bit of data analytics managing you know ad hoc reporting and so forth… I have…two programmers …who (are)…pulling data from…data sources, but I also can do that as well, so I'm not always reliant on a programmer analyst (except) for the big projects," (Participant #2) "I had more of a technical background than anyone else in the office, so I was (initially) responsible for developing the technical aspects and working to get what we needed and I can basically continued that model, as I moved into administration and (as I) brought people on I just kept talking to them and utilized their expertise."(Participant #6).
Informs Admin/Tech staff of Data Implications.	"…I have the liaison role, and so, then I will consult with the Vice President, and the President about the (SACCS) standards and all that/…when… (the analyst) started here…we had to sometimes remind her to think about…put some thought into the analytics part because …I had to get her to think in terms of…the inner workings of the strategic planning process and…" (Participant #11) "if the program director needs their assessment data analyzed in a way that will speak to the language of the stakeholder, I can write the analysis up and pull whatever data from the system to do that analysis… summarizing course valid data, I have some tools I use to take all the data and make it easier for the Deans to, to print out and use…and analyze" (Participant #4)
Collaborates Across Institutional Departments (e.g Achieving the Dream)	"so we just ran an initiative with Achieving the Dream… the data committee…is made up of faculty…so…we talk about what data should (we pull)… (then ask them) what do you see in that data? What is in that data that I didn't see, or can we begin to help one another interpret it?" (Participant #7). "we do have like a data team (across departments), so we do have a team of like myself, as well as some of the Deans and some of like the registrar…academic affairs, student services, registrar… we have a group of people that can come together…and discuss it…so we can kind of all work together to come up with solutions". (Participant #9).

specifying as to what, or how many types of software are being utilized. Second, the second theme involved "IR professionals", in contrast with the first theme which only included IR directors. The point of this differentiation was to demonstrate that administrators, as well as directors, can utilize multiple types of data analytic software.

Nevertheless, like the previous theme, the second theme also involved RQ1 concerning the ability to manage knowledge by utilizing data analytical systems for improved decision-making. According to most participants, IR professionals, including directors and administrators, to varying degrees could utilize the following data-analytic software systems: Power BI, Banner, Argos, Excel, SQL Server and SPSS. *"…what I do is I extract data with Argos which is like a sequel based Program…And then I put it into SPSS to do my actual analyses of it, so I built a lot of coding like as far as syntax sequel coding that type of stuff and that's the IR side of things…we use Power BI for the visualizations… now I can use it (Argos) to pull from Banner also."* (Participant #9). "*…In Argos…you can download (the report) as an Excel file or whatever so that's... kind of our…primary method…I may take it and put it into Power BI, so that people will not have to look at the spreadsheet…they can look at a kind of a more robust picture of the data, then just read the numbers."* (Participant #3). Table 7 below identifies each code of this theme and provides several corresponding excerpts from participants regarding IR professional confidence with utilizing data analytic systems for institutional decision-making.

Theme 3. Improved Student Success Achieved through Visualization

The third theme that emerged from this study was improved student success achieved through visualization. Improved student success through visualization was defined as any improvements to student success including graduation, retention, or course performance

Table 7. Theme 2. Codes and Interview Excerpts.

Codes	Interview Excerpts
• Banner • Argos • SQL Server • SPSS	"…what I do is I extract data with Argos which is like a sequel based Program…And then I put it into SPSS to do my actual analyses of it, so I built a lot of coding like as far as syntax sequel coding that type of stuff and that's the IR side of things…we use power bi for the visualizations… now I can use it (Argos) to pull from Banner also." (Participant #9).
• Banner • Argos • SQL Server • Power BI	"In general, I…mentioned Argos, obviously…Banner, which is information system, which is collecting the data, you know…that collects most information…I can write SQL to produce or pull data…and then you're gonna pull those into Excel…and then use Power BI… I don't find SQL as a great way to model data. I can model data better in Power BI." (Participant #4)
• Banner • Argos • SQL Server • Excel	"I personally am just a huge excel person…I do a lot I do a lot to SQL scripting straight out… and it pulls the same information as if I went into Argos …so it just depends on what I'm doing and how quickly I need it… sometimes (I pull) directly from Banner, sometimes I'll pull it out of Argos instead, so it just depends". (Participant #2)
• Excel • SPSS	"Before I had a staff, I did quite a bit of it (utilizing data analytic systems), and it was primarily using Excel, SPSS and the (pulling) data files that come out of the (old) student information system (blackboard)…" (Participant #6)
• Power BI • Excel	"…In Argos…you can download (the report) as an Excel file or whatever so that's... kind of our…primary method…I may take it and put it into Power BI, so that people will not have to look at the spreadsheet…they can look at a kind of a more robust picture of the data, then just read the numbers." (Participant #3).
• SPSS • Power BI	"I'm mostly focused on SPSS…, so I'm very… familiar with it…however, if I need to, in general, as far as the…analytics, I'll do… visualization, I use a Power BI". (Participant #5)

because of decisions or initiatives resulting from data visualization. This theme corresponds to RQ1 pertaining to knowledge management when utilizing data analytical systems for institutional decision-making. According to the participants, one type of data analytical platform that provided improved decision-making for student success was from data visualizations. One participant described how their institution began utilizing visualizations, as well as the resulting response from their staff following that experience, and how it impacted their initiatives for student success: *"when we first started with it (visualizations) we were going to do a presentation on student retention…at the end of the first semester (it showed) 17 out of 100 (students) will be gone, and then, at the end of the first fall, the fall retention, 50 of them are gone…and we visualized…there's really…(only) about 23 out of every 100 students graduate and… so (now) we have dashboards that are housed in our portal, we've built them on all of the KPI's associated with strategic planning…(and now) we've got one built on course success rates… so our faculty and staff use it a lot"* (Participant #7).

Participants also thought dashboards helped administration better understand student success issues from the data: *"I'm using Power BI to look at…core success and completion trends over the past five years…student performance and student outcomes (and) along with those metrics…allows them (administration) to ask more specific questions about, okay, let's look at, you know, this is pointing to this instructor let's go look at their course…talk to the Dean about this, you know it's it provides a good jumping off point.."* (Participant #4). Moreover, dashboards can help identify at-risk populations who need additional academic help: *"…And then we had a faculty Member who built a Power BI dashboard for student success, broken down by those focus populations and so it's information that now the campus has access to, you* *can see it, you know from a variety of different curiosity questions you can just kind of go in and explore the information"* (Participant #2). The following table identifies each code of this theme and provides several corresponding excerpts from participants regarding improved student success achieved through visualization.

Theme 4. Ambivalence towards Dashboards Providing Greater Access to Data

The fourth theme derived from this study was an ambivalence toward how dashboards provided greater access to data within the institutions, and therefore provided more informed decision-making. This theme was defined as the mixed views expressed by participants regarding the level of data accessibility from analytical systems that are needed for institutional decision-making, including the levels of access departments experience outside of institutional research such as faculty, and staff. This theme refers to both RQ3 and RQ4 when considering institutional culture barriers, and how to navigate institutional culture barriers when sharing data or collaborating with other departments to enhance institutional decision-making, respectively. Institutional culture barriers can potentially involve data governance structures and policies, operational processes, and the underlying assumptions of institutions pertaining to sharing or collaborating across other departments outside of institutional research.

Some participants reported that dashboards only gave access to the data they needed, and that most faculty and staff can access this data through dashboards, albeit with some limitations: *"we have a data governance policy that's published and it's structured…we've (IR department) pretty much got access to all data… (however) only faculty and staff have access to certain dashboards."* (Participant #7). *"(dashboards are) restricted to department chairs and*

Table 8. Theme 3. Codes and Interview Excerpts.

Codes	Interview Excerpts
Student Success Initiatives	"when we first started with it (visualizations) we were going to do a presentation on student retention… …and we visualized…there's really…(only) about 23 out of every 100 students graduate and… so (now) we have dashboards that are housed in our portal, we've built them on all of the KPI'S associated with strategic planning…(and now) we've got one built on course success rates…" (Participant #7). "We have several leaders that go through the data…(they conduct) course outcome analysis that's one of the things that they've really been heavily using visualizations." (Participant #6).
Administrative Understanding of Student Data	"I'm using Power BI to look at what are core success and completion trends over the past five years…student performance and student outcomes (and) along with those metrics, which then allows them (administration) to ask more specific questions about, okay, let's look at, you know, this is pointing to this instructor let's go look at their course…talk to the dean about this, you know it's it provides a good jumping off point.." (Participant #4).
Identify At-Risk Students	"…And then we had a faculty Member who built a Power BI dashboard for student success, broken down by those focus populations and so it's information that now the campus has access to, you can see it, you know from a variety of different curiosity questions you can just kind of go in and explore the information" (Participant #2). "…another project is a diversity dashboard which you've got a lot of growth in terms of you know, like student retention and success by each of the race and ethnicity categories or the cost of Pell eligible students…that that will help us…identify and see where our gaps are and we can help students…"(Participant #8).

above (not faculty)…its only restricted if they (department chairs) want to compare their data with another department”. (Participant #4).

Some participants also revealed that dashboards encouraged additional staff to be more involved with data who would otherwise not utilize it: *“(dashboards) provide data information to more staff, gets staff and administration bought-in to using data…administration can use dashboards and filters to answer questions instead of calling IR”*. (Participant #3). *“(Dashboards) made data much more accessible to administration…giving them a broader perspective and (they) don’t’ have to ask us (IR department) for every answer regarding institutional data”.* (Participant #6).

Lastly, some participants stated that the data provided by dashboards are progressively becoming more accessible to all staff. This notion carried mixed responses from the participants. Some participants were optimistic and thought that dashboards provided a point of navigation around barriers to data access: *“So…(dashboards are) mostly restricted to just the directors and above… but we're moving towards building (more) dashboards…that's something that we want to be able to do so that every department can come and look at…their department, as a group…”* (Participant #5). In contrast, other participants were more skeptical when considering how dashboards provided greater access to data and viewed it as a potential barrier to knowledge management by making data less secure: *“You know, if I'm speaking candidly, we actually probably should be locking things down more than we have things open right now. It's actually probably too open with Power BI data access between departments”.* (Participant #4). Similarly, another participant mentioned that having progressively open access to data via dashboards could be a problem without data governance policies in place. *“The* *administration uses data visualizations… there is no data governance structure…we solve data governance through personal discussions with other departments… we are moving to a centralized cloud host so…potentially…data governance could be an issue."* (Participant #2). The following table identifies each code of this theme and provides several corresponding excerpts from participants regarding the ambivalence of participants towards dashboards providing greater access to data for institutional decision-making.

Theme 5. Ambivalence towards the Effectiveness of Predictive Analytics in IR

The fifth primary theme of this study was an ambivalence toward utilizing predictive analytics in IR. This theme was defined as the mixed views expressed by participants concerning the potential effectiveness of using the various statistical techniques employed by predictive analytics to analyze current and past institutional data to improve student outcomes. The statistical techniques of predictive analytics include data mining, predictive modeling, statistical algorithms, and machine learning. This theme is also related to RQ1 regarding the ability to apply knowledge management by effectively utilizing predictive analytics for institutional decision-making, as well as RQ3 and RQ4 pertaining to the institutional culture barriers from the skeptical attitudes of some participants with the effectiveness of predictive analytics, as well as how to navigate these cultural barriers when sharing or collaborating with other departments to conduct predictive analytics.

The topic of predictive analytics was very polarizing among the participants, as some strongly supported the use of predictive analytics while others were very skeptical of its effectiveness with improving student success outcomes by providing unintentional barriers to knowledge management. One major reason some participants are skeptical of predictive

Table 9. Theme 4. Codes and Interview Excerpts

Codes	Interview Excerpts
Open Data Access with Minor Limitations	"we have a data governance policy that's published and it's structured…we've (IR department) pretty much got access to all data… (however) only faculty and staff have access to certain dashboards." (Participant #7). "So…(dashboards are) mostly restricted to just the directors and above… but we're moving towards building (more) dashboards…that's something that we want to be able to do so that every department can come and look at…their department, as a group…" (Participant #5).
Data "Buy-In" from Faculty	"(dashboards) provide data information to more staff, gets staff and administration bought-in to using data…administration can use dashboards and filters to answer questions instead of calling IR". (Participant #3). "(Dashboards) made data much more accessible to administration…giving them a broader perspective and (they) don't' have to ask us (IR department) for every answer regarding institutional data". (Participant #6).
Data Access Needs Limitations	"You know, if I'm speaking candidly, we actually probably should be locking things down more than we have things open right now. It's actually probably too open with Power BI data access between departments". (Participant #4). "The administration uses data visualizations… there is no data governance structure…we solve data governance through personal discussions with other departments… we are moving to a centralized cloud host so…potentially…data governance could be an issue." (Participant #2)

analytics is that collecting data lacks feasibility: *"I'm very skeptical that there's a type of data we collect in education that…is actually much to monitor… maybe there's…some early warning signs you can get but then you need (all the) professors and you need (all the) people on the ground (to enter the data to be reliable)"* (Participant #4).

Another reason for the general skepticism comes from the possibility that in order to make predictive analytics feasible, data collection, and perhaps even the interventions based on those findings, might need to be mandatory: *"To make something (like data entry/collection) mandatory, faculty might not like it, it (predictive analytics) would be difficult to enforce"* (Participant #7). In addition to the possibility of mandatory data collection and interventions are the potential student privacy issues: *"You know if the result of predictive analytics is mandatory advising, you (potentially) have intrusive advising. (Early warning mechanisms are) getting into like privacy issues and surveillance…"* (Participant #4).

Furthermore, some participants think there is a general lack of understanding with predictive analytics amongst higher education administration: "*my take is people don't understand what predictive analytics are, that's my biggest one, because…we need to start tracking so that we can use predictive analytics two to three years in the future, and I think…that's a lot…people don't understand is that, you know, you need to develop data and have rich data in order for predictive analytics to work".* (Participant #8).

Despite these potential challenges however, other participants supported the implementation of predictive analytics in institutional research. Furthermore, they viewed the expansion of predictive analytics in IR as improving knowledge management*"…it's (institutional* *research) moving from actual data analytics to the predictive data, you know this time and age we need to be more proactive than reactive…we need to do this to improve, and… everybody wants to know about (the predictive power of) classroom size (with student success), so it helps with that* (Participant #5).” Other participants supported this position, viewing predictive analytics as a “next-step” to improve the function of the institution and help students succeed: *“there's a big push, we were really trying to attack the student success issue you know, who needs help when they need help, but because we know…they (students) have an aversion to asking for help…how do we figure out whether or not they need it, so we need a lot of that real-time kind of analytics but…we're not equipped for that yet”*. (Participant #2).

Participants who were more supportive of predictive analytics were also very complimentary of early-warning systems that identify struggling or at-risk students in order to redirect them into new majors or course paths as evidenced by the subsequent interview passages: *“… (predictive analytics) allows for more specific course paths (during the enrollment process), advanced math, remedial English, (for one student) instead of one size fits all”*. (Participant #5). “*Early warning (helps) advise them into a new major… student success rate leads to state appropriation, this leads to a demand for more predictive analysis in Community Colleges”* (Participant #6)”. The following table identifies each code of this theme and provides several corresponding excerpts from participants regarding ambivalence towards the effectiveness of predictive analytics in IR.

Theme 6. Navigating Knowledge Gaps between IR Staff and Administration

The sixth identified theme of this study referred to how participants navigated knowledge gaps with their departmental staff based on their differing job positions and skill

Table 10. Theme 5. Codes and Interview Excerpts.

Codes	Interview Excerpts
Lack of Feasibility	"To make something (like data entry/collection) mandatory, faculty might not like it, it (predictive analytics) would be difficult to enforce" (Participant #7).
Lack of Student Privacy	"You know if the result of predictive analytics is mandatory advising, you (potentially) have intrusive advising. (Early warning mechanisms are) getting into like privacy issues and surveillance…" (Participant #4).
Lack of Admin/Staff Understanding	"my take is people don't understand what predictive analytics are, that's my biggest one, because…we need to start tracking so that we can use predictive analytics two to three years in the future, and I think…that's a lot…people don't understand is that, you know, you need to develop data and have rich data in order for predictive analytics to work". (Participant #8).
• Improves IR Department Function • Predicts Students Outcomes	"…it's (institutional research) moving from actual data analytics to the predictive data, you know this time and age we need to be more proactive than reactive…we need to do this to improve, and… everybody wants to know about (the predictive power of) classroom size (with student success), so it helps with that (Participant #5)." "there's a big push, we were really trying to attack the student success issue you know, who needs help when they need help, but because we know…they (students) have an aversion to asking for help…how do we figure out whether or not they need it, so we need a lot of that real-time kind of analytics but…we're not equipped for that yet". (Participant #2).
Identify At-Risk Student (Monitors & Tracks Performance)	"Early warning (helps) advise them into a new major… student success rate leads to state appropriation, this leads to a demand for more predictive analysis in Community Colleges" (Participant #6)".

sets. Navigating the knowledge gaps of the IR department staff is defined as any actions taken by the participants to understand the more technical applications of data analysis used by the technical staff, and/or assisting the technical staff with understanding the administrative applications of the data analytical findings. This theme was linked to RQ1 regarding IR director's ability to improve their own technical ability and RQ2 concerning how IR directors navigate these institutional knowledge gaps when collaborating with their technical staff by including or informing them of information in administrative meetings.

Participants often indicated that understanding the duties of technical staff can be achieved through effective communication. *"Oftentimes what I bring to the discussion (with my staff) is what data do we need to answer the question… and (ask) what else might they (admin) want to know once we answer this question …they (staff) can tell me what the code means you know that sort of thing, so I feel like we meet pretty well in the middle there"* (Participants #2). One concern of directors and administration is that technical staff might have difficulty understanding the implications of their data findings on an institutional level and therefore reduce the impact of decision-making. One participant explains how they assist their staff with comprehending the overall administrative strategy: *...my staff serve on committees that are college wide and so they understand…the big picture…after I come out of a senior staff meeting I tell them…what we've talked about…but, more importantly, we begin to build relationships, so instead of a person saying I need this piece of data…they (staff) call them and say what research question are you trying to answer and then they (staff) talk through with them about what data they need it's much like a dissertation…* (Participation #7). The following table identifies each code of this theme and provides several corresponding excerpts from participants regarding navigating knowledge gaps between IR staff and administration.

Theme 7. Training Needs Met or Unmet with Data Utilization

The seventh theme of this study was training needs met or unmet with data utilization. This theme is defined as implementing, or not implementing, the action of teaching a person a particular skill such as analytical software utilization or the application of findings from analytical software. This theme coincided with RQ1 when considering the ability to manage knowledge through additional training in software and administrative skill sets to utilize data analytical systems for institutional decision-making. This theme is also related to RQ2 with navigating knowledge gaps of technical staff for big picture strategic initiatives. Moreover, this theme is also related to RQ3 and RQ4 when addressing and navigating institutional culture barriers such as the underlying assumption that no data is available to other departments and therefore cannot be accessed, which negatively impacts sharing and collaborating with data across an institution.

Some participants reported that staff outside of their department would benefit from Argos software training because it was being underutilized. Argos is a reporting software tool available to most departments outside of IR which can access institutional data but requires SQL coding to extract the data: *“…and then also make them (staff of other departments) aware that there is an Argos report that you…have access to, that you can do that yourself…some of that is training, education…not enough of the campus is aware of what's available to them.” (Participant #2). “So generally folks (staff of other departments) have access to the data (in Argos). Do they know how to get it? Not always… I think that's a bigger issue, as in a training*

Table 11. Theme 6. Codes and Interview Excerpts.

Codes	Interview Excerpts
Directors Understand Duties of Technical Staff Through Effective Communication.	"Oftentimes what I bring to the discussion (with my staff) is what data do we need to answer the question… and (ask) what else might they (admin) want to know once they answer this question …they (staff) can tell me what the code means you know that sort of thing, so I feel like we meet pretty well in the middle there" (Participants #2). "Communicating with…staff for results of the analysis and with other folks who are maybe not as technical…that's something I've had to learn to get better at over time and trying to figure out…how processed the data needs to be…It's just a matter of getting to know who knows what and…how different folks want to use data". (Participant #4). "I had been…doing a lot of data analysis...so I…come up with three or four solutions…that makes it easier because…it gives the analyst…options on how they want to go…they'll pick one, we'll start working on it…somewhere in the process, I'll…shoot him a small little data visual…(and say) Is this what you're wanting and…we can tweak it from there." (Participant #5).
Tech Staff/Directors Can Better Impact the Application of Data when Included/Updated regarding Administrative Meetings	"I always encourage them (staff) to think beyond just the task…now, are they involved in the higher-level discussions…not as much…(but) there are times when I when I pull them in (to the higher-level discussions)". (Participant #3). ...my staff serve on committees that are college wide and so they understand…the big picture…after I come out of a senior staff meeting I tell them…what we've talked about…but, more importantly, we begin to build relationships…they (staff) call them (committee) and say what research question are you trying to answer and then they (staff) talk through with them about what data they need (Participation #7). "…we have other institutions where they only call their data IR folks into the meeting when they actually need them to be there, I would argue, (that) strategy is not great, because …you're probably not going to get as much out of that as you could otherwise… to bring an IR person and ask them how they're going to assess it…to make sure that when it comes time to do the evaluation that there is a way to do it". (Participant #10)

issue". (Participant #4). Similarly, another participant wanted more training in how to apply data findings on an institutional level: *"It's more than just the ability to analyze data, you have to be able to learn the culture of the place where you're doing that and…to be able to do it well…the challenge is for us…specifically would be more training for faculty and staff*. *I think its both, but I think it is almost more in application".* (Participant #7). The following table identifies each code of this theme and provides several corresponding excerpts from participants concerning met or unmet training needs with data utilization and application.

Overarching Perspectives Related to Theoretical Framework

Knowledge Management Perspectives

Knowledge Management is referred to by the participants in several themes including Improved Student Success Achieved through Visualization, Ambivalence towards the Effectiveness of Predictive Analytics in IR, Navigating Knowledge Gaps between IR Staff and Administration Regarding Data Utilization, and Training Needs Met or Unmet with Data Utilization. Some specific examples of improved knowledge management include participants improving upon their own ability to interpret data findings, which will help them interact more effectively with technical staff and promote a more informed decision-making process with their additional input during administrative meetings (Hawkins, & Bailey, 2020). In the context of knowledge management theory, improving data interpretation skills lends itself to converting implicit knowledge or applicable knowledge, to explicit knowledge which can be articulated to other IR professionals (Lehman, 2017). Likewise, improving data analysis skills coverts : *"So I grew up working in an area where we had to learn how to learn it (technical skills) on the job… I…picked up with the data quickly you know I'm able to do both (administrative and*

Table 12. Theme 7. Codes and Interview Excerpts.

Codes	Interview Excerpts
Unmet Argos Software Training	"…and then also make them (staff of other departments) aware that there is an Argos report that you…have access to, that you can do that yourself…some of that is training, education…not enough of the campus is aware of what's available to them." (Participant #2). "So generally folks (staff of other departments) have access to the data (in Argos). Do they know how to get it? Not always… I think that's a bigger issue, as in a training issue". (Participant #4).
Unmet Administrative Skills Training	"It's more than just the ability to analyze data, you have to be able to learn the culture of the place where you're doing that and…to be able to do it well…the challenge is for us…specifically would be more training for faculty and staff. I think its both, but I think it is almost more in application". (Participant #7).
Met Power BI Training	"…if they (administration) notice, something that looks really unusual, maybe, for instance, they might call or ask us…can you verify that this is correct… but yeah, I mean it's pretty much you know, trying to train them to use it (Power BI) and trying to make sure that they understand it." (Participant #9).
Met Customized Administrative Application Training	"Well, you can build a notebook (One Note) and so you can copy and paste…import files…create a forum and… do links…for our SACS assessment collection instead of paying for this…real expensive product, and…we would export files…as a PDF…I'm just training the academic Deans on how to use it and they can input their program objectives and they're learning outcomes… I'm (also) training all the academic folks…and then the administrative (departments)…that's part of strategic planning as well …as SACS". (Participant #11)

technical)… But we are able to advise when it comes to the you know all things SACS…when it comes down to critical information and critical decisions". (Participant #11).

IR professionals can also improve their knowledge management by sharing findings with other departments during collaborative projects, which initiates the process of creating new knowledge by transforming explicit knowledge to more implicit knowledge (Steyn, 2004). A current example of this is implementing the "Achieving the Dream" initiative which, as mentioned earlier, was created to address equity issues in community colleges: *"so we just ran an initiative with Achieving the Dream…where one of my analysts was the chair of the data committee and then the rest of community is made up of faculty…so what we would do is talk about what data should (we pull)…then we meet again and with the Faculty… (then ask them) what do you see in that data? What is in that data that I didn't see, or can we begin to help one another interpret it?* …we have done a pretty good job of training the College Community college community." (Participant #7).

Institutional Culture Barriers Impacting Knowledge Management

Impacts on knowledge management by institutional culture barriers were alluded to by participants in several themes including Ambivalence towards Dashboards Providing Greater Access to Data, Ambivalence towards the Effectiveness of Predictive Analytics in IR, and Training Needs Met or Unmet with Data Utilization. One type of culture barrier that negatively influences sharing or collaborating on data analytical projects for institutional decision-making are from the "underlying assumptions" of institutions (Schein, 2010). Some of these underlying assumptions may assume a lack of value, or even the lack of existence, of available data, and therefore administrators will not share or receive data findings (Serban & Luan, 2002). This was evident by a tendency of some administrators to avoid focusing on data-informed collaboration and exclude IR reps during administrative meetings: *"…we have other institutions where they only call their data IR folks into the meeting when they actually need them to be there, I would argue, (that) strategy is not great, because …you're probably not going to get as much out of that as you could otherwise… to bring an IR person and ask them how they're going to assess it, you know you've probably already missed your opportunity …to make sure that when it comes time to do the evaluation that there is a way to do it".* (Participant #10).

An additional underlying assumption found in this study was a participant assuming a lack of cooperative relationships from staff outside of their own department due to either the hierarchical structure of the organization or from simply the lack of a collaborative atmosphere conducive to data sharing (Serban & Luan, 2002). This was evident from one participant stating: *"what's frustrating, sometimes, though, is to go to the conferences and be involved and see what's going on with our schools and how approaches that are working, whether it's in academics or for student affairs (and to) come back with these great ideas and then you want to share and say oh wait, maybe you should do this, but then you can't really do much because you're not in academics, you're not in student affairs, you know you just kind of say, well, this is a great idea if you're interested or this worked for this school or this worked for this group, you know so that's what's hard, because we are a kind of like that…the office it's "off to the side", and we have a bird's eye view of the College in the inner workings, but yet we're not a part of the other groups when it comes to having major influence".* (Participant #11).

Another type of institutional culture barrier are the "espoused beliefs and values" of an institution which include the established operational processes such as data governance

(Schein, 2010). An example of restrictive data governance was apparent from one administrator when trying to extract and analyze data regarding non-credit courses: *"One project in particular that's coming up is taking the non-credits… either it's a banner or into a system that complements banner and we're fighting…all these processes that we already have in place…(a) two week excel course or maybe these workforce kinds of development courses which are…huge for the Community college sector…and going to get larger, quite frankly, so that's why I believe that that project in particular may go up a level".* (Participant #8). The figure below represents the impact of institutional culture on knowledge management including that of underlying assumptions and espoused beliefs and values of an institution.

Responses to Research Questions

All four research questions were answered by the participant responses. The following are a summary of those responses for each research question.

RQ1. What are the perspectives of IR professionals regarding their ability to apply knowledge management (e.g., analyzing, interpreting, sharing, collaborating) when utilizing data analytic systems (e.g. visual analytic systems) to impact institutional decision-making?

Most IR directors were confident when expressing their ability to apply knowledge management when utilizing data analytic systems for institutional decision-making. As a "liaison", or intermediary, between administration and technical staff, they stated that it was imperative for them to possess a varied skill set to manage knowledge not only for data analysis and other technical job functions, but also with applying the implications of the data findings to all levels of staff. This was evident in the following themes of the study: IR Director Confidence

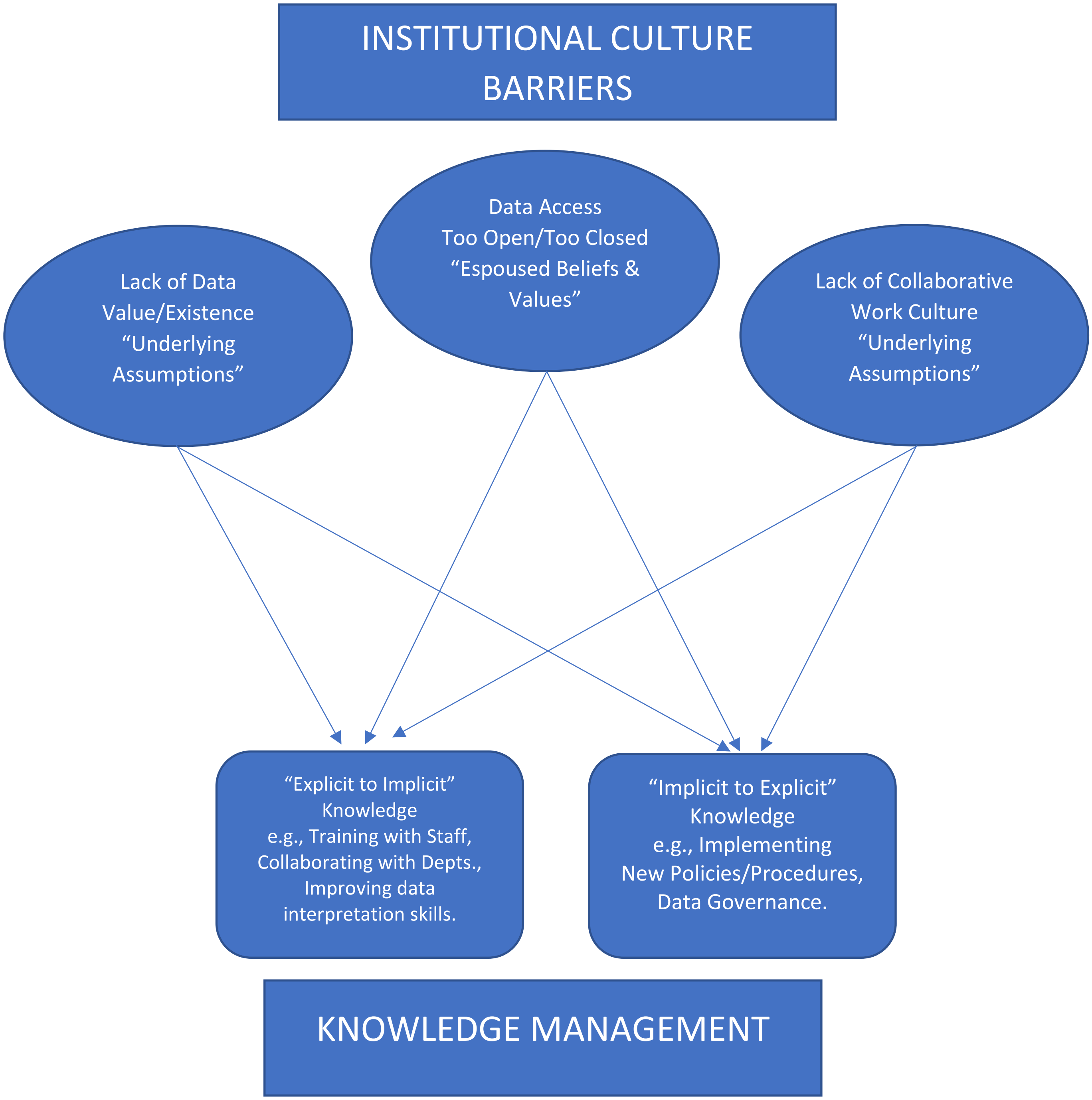

Figure 1. The Impact of Institutional Cultural Barriers on Knowledge Management

with Knowledge Management Ability, IR Professional Confidence with Utilizing Data Analytic Systems for Institutional Decision-Making, Improved Student Success Achieved through Visualization, and Navigating Knowledge Gaps between IR Staff and Administration with Data Utilization.

Codes related to these themes also covered a diverse range of knowledge management skills such as utilizing several types of data-analytic software or by contextualizing the raw data for technical staff to demonstrate implications for strategic planning initiatives. In addition, IR directors would also utilize dashboards and visualizations when presenting data to help administrative staff understand institutional needs and trends. Furthermore, IR directors use these previously mentioned data analytics skill sets when spearheading and collaborating on cross- departmental data-related initiatives such as “Achieving the Dream”. These examples clearly demonstrate a sufficient response to the first research questions in that IR directors certainly can manage multiple sources of knowledge for institutional decision-making by utilizing data analytic systems.

RQ2. How do IR professionals navigate institutional knowledge gaps (e.g., analytical vs. interpretive; technical vs. operational) when collaborating with other IR professionals by utilizing data analytic systems to impact institutional decision-making?

Like the previous response to RQ1, IR directors indicated that they had a strong impact with navigating institutional knowledge gaps of IR department staff by utilizing data analytic systems to impact institutional decision-making. Again, this perceived impact by IR directors was connected to the theme of IR Director Confidence with Knowledge Management Ability by playing the role of “liaison”, intermediary, or mediator when communicating the data implications to both their technical staff and administration. In addition, this impact was also indicated in the theme of Navigating Knowledge Gaps between IR Staff and Administration with Data Utilization, in that to bridge these knowledge gaps IR directors must utilize data analytic systems using two different strategies when interacting with technical staff and administration. To relate with technical staff for example, IR directors will first utilize data analytic systems to understand the raw data findings and then, in conjunction with their administrative skills, bridge the knowledge gap with technical staff to help them understand larger scale strategic initiatives by giving context to the data, in addition to either including or informing them of the implications from administrative meetings. In contrast, IR directors will utilize dashboards and visualizations to help administration understand the implications of data findings during administrative meetings.

Furthermore, these findings also answered this research question by uncovering a need for IR administrators to include IR directors and staff more often during administrative meetings, even if administrators assume that their presence is unnecessarily. Moreover, and to a lesser degree, this research question was also answered from the theme of Training Needs Met or Unmet with Data Utilization in which administrative skills need to be taught to both IR directors and technical staff to bridge staff knowledge gaps by understanding larger scale strategic initiatives. Ultimately, responses to this research question were adequate in portraying how knowledge gaps are navigated by utilizing data-analytics systems for institutional decision-making.

RQ3. What institutional culture barriers (e.g., policies, operational processes, relevancy, conduciveness) do IR professionals encounter when sharing data or collaborating with other departments to enhance institutional decision-making?

One theme pertaining to this research question was the Ambivalence towards Dashboards Providing Greater Access to Data. Despite the skepticism of some, generally most participants thought that the potential culture barrier of data governance was either not an issue and/or unnecessary due to a lack of formal governance processes at their institution. Conversely, some participants thought the lack of data governance was an institutional culture barrier itself, as it was perceived to decrease data security and thus adversely affecting their knowledge management ability.

The most prominent theme related to institutional culture barriers when sharing or collaborating with other departments to enhance institutional decision-making was the theme of Ambivalence towards the Effectiveness of Predictive Analytics in IR. Clearly, predictive analytics was the most polarizing topic in this study for various reasons. In terms of institutional culture barriers however, the lack of resources for acquiring knowledge from the current technology was cited as an issue (Schein, 2010). In other words, the technology might be available, but utilizing the statistical procedures of predictive analytics (i.e. data mining, statistical algorithms, machine learning) for IR was not available or had not been approved by the administration perhaps due to policy concerns. However, probably the most notable institutional culture barrier to predictive analytics came from the underlying assumption that staff may simply assume a lack of value from using it in IR due to the following problems:

potential issues with student privacy, a lack of feasibility due to the time needed to build a reliable and valid data set, and a lack of buy-in or compliance from faculty.

There are other examples of institutional culture barriers not related to any primary themes mentioned in the previous section regarding Institutional Culture Barriers Impacting Knowledge Management. Most notably, the lack of presence in administrative meetings from IR staff. Even so, the most prominent institutional culture barriers were experienced when considering predictive analytics for utilization in IR. Overall however, institutional cultural barriers appear to be on the decline according to the study participants as evidenced by an ever more accessible data environment within their institutions. Overall, the responses to this research question satisfactorily identified the presence (or lack thereof) of institutional culture barriers that IR professionals encounter when sharing data or collaborating with other departments to enhance institutional decision-making.

RQ4. How do IR professionals navigate institutional culture barriers (e.g., policies, operational processes, relevancy, conduciveness) when sharing data or collaborating with other departments to enhance institutional decision-making?

When attempting to conduct data projects across departments there is sometimes an institutional culture barrier from the underlying assumption of an atmosphere not conducive to data collaboration. The responses to this research question are derived mainly from the theme of IR Director Confidence with Knowledge Management Ability. The “Achieving the Dream” initiative has been integral in fostering positive collaboration across departments with data projects in 2-year institutions. Many participants reported that they, or their technical staff, lead cross departmental data teams in which every department has at least one technical staff person. Moreover, these collaborative data projects identified achievement gaps with underserved student groups and helped to set and measure goals regarding student success outcomes.

Relatedly, when attempting to collaborate across departments there is also an institutional culture barrier from the underlying assumption that staff may assume a lack of existence of available data (Schein, 2010). This underlying assumption is related to the theme of Training Needs Met or Unmet with Data Utilization, and more specifically with the code of Unmet Argos software training. Argos is a reporting tool which can access student data relevant to the Achieving the Dream initiative, and some participants stated that Argos is available to most departments across their institutions and contend that most institutional staff are not aware of the practical utility of Argos. Furthermore, those staff that are aware of Argos cannot utilize the software as it requires SQL coding to extract data. Therefore, participants argue that institutional staff could benefit from a training program which would improve data access across departments and would make collaboration more productive and efficient. In conclusion, cross-divisional data teams from Achieving the Dream with additional training are responses to this research question that appropriately describe methods in which IR professionals navigate institutional culture barriers when sharing data or collaborating with other departments to enhance institutional decision-making.

Findings Summary

Participant responses produced many distinct, significant, and relevant answers to the research questions of the study. One of the most fitting responses for the first research question was how the IR directors reported that gaining technical knowledge had greatly improved their knowledge management. Secondly, having a highly knowledgeable IR director or administrator will inevitably assist technical staff with any knowledge gaps understanding the broader scale initiatives by contextualizing the data as referred by the second research question. However, having a more informed staff includes having them regularly present in administrative meetings which not only responds to the second research question pertaining to navigating knowledge gaps by both directors and technical staff, but also answers the third and fourth research questions as well, which would help sidestep any preconceived institutional barriers from underlying assumptions concerning the value of data from administrators. Lastly, providing additional software training can help staff outside of IR access their own data and improve collaboration with IR directors on larger scale data projects, overcoming the institutional culture barrier from the underlying assumption of a lack of existing data. Implementing additional training would also answer the third and fourth research question.

It should be noted that participant responses to both RQ3 and RQ4 did not correspond entirely, especially with themes 4 and 5, when considering the mixed responses with expanded data access and predictive analytics, respectively. Meaning, that some cultural barriers identified by participants in RQ3 did not necessarily have a corresponding solution explicitly stated in RQ4. Likewise, solutions identified to overcome certain cultural barriers in RQ4 did not neccearily have the corresponding barriers mentioned by the participants in RQ3. This was particularly true for interventions which had been implemented for an extend period such as the Achieving the Dream initiative. In the case of the former (i.e., the barrier was identified but not the solution), recommendations were given later in this chapter concerning how to implement solutions to these barriers. Conversely, in the case of the latter, (i.e., no barrier mentioned, but participants identified a solution) barriers were only mentioned generically such as “a lack of data sharing and collaboration”.

Furthermore, RQ3 and RQ4 did not always correspond internally, meaning that participants had differing opinions regarding whether certain interventions were a barrier or solution. In both themes 4 and 5 for instance, participants had conflicting views regarding whether the expansion of data access and predictive analytics was a cultural barrier or a solution to a cultural barrier. Nevertheless, the recommendations given in chapter 5 will attempt to reconcile these supposed contradictory responses. The following chapter provides recommendations based on the study findings.

Chapter 5. Discussion and Recommendations

The following chapter discusses the findings from this study and gives recommendations regarding how to improve the impact of data analytic systems on institutional decision-making. This chapter begins with a summary of the findings from the previous chapter followed by a comparison of those findings with the current literature. This chapter will then make recommendations concerning how to better utilize data analytics to impact institutional decision-making. These recommendations include strengthening data governance for dashboards and data visualizations, expanding predictive analytics to further student success, and data literacy training. Lastly, the limitations of this study will be discussed followed by some concluding remarks pertaining to this study.

Summary of Findings

The findings from this study generated several themes that were characterized by either unimpeded knowledge management, or by limited knowledge management from organizational culture barriers. Themes that expressed unencumbered knowledge management included: IR Director Confidence with Knowledge Management Ability, IR Professional Confidence with Utilizing Data Analytic Systems for Institutional Decision-Making, Improved Student Success Achieved through Visualization, and Navigating Knowledge Gaps with IR Staff and Administration with Data Utilization. In contrast, themes that consisted of impediments when applying knowledge management included Ambivalence towards Dashboards Providing Greater Access to Data, Ambivalence towards the Effectiveness of Predictive Analytics in IR, and Training Needs Met or Unmet with Data Utilization. All research questions were sufficiently answered by one or more of the study themes.

Findings and the Current Literature

This study consisted of findings that both supported and were contrary to the current literature. One aspect from this study that supported the literature was that data-informed decision-making was currently utilized and promoted to a far greater capacity than data-driven decision-making. This was made evident by the participants when stressing a need to contextualize the data findings to their individual institutions and not to rely just on the data itself (Winkler & Fyffe, 2016). Contextualizing raw data was particularly apparent by the descriptions of the IR directors with respect to their interactions with technical staff or administration. Given their position, IR directors typically have the best overall grasp for the data implications of their institution being familiar with both the administrative strategic planning and the raw data generated by the technical staff. Having this vantage point gives IR directors a unique perspective which can more effectively guide the administration and thus the overall direction of their institution.

Other aspects of the literature supported by this study in relation to data-informed decision-making was a general lack of confidence from administrators regarding its importance (Gagliardi, Espinosa, Turk, & Taylor, 2017), and whether it can be utilized effectively by their institution (Jaschik & Lederman, 2019). This lack of confidence towards data with influencing decision-making was made apparent when it was reported that IR staff were sometimes excluded from administrative meetings due to the assumption that they were only needed for an explanation of data findings and not for strategic planning.

Furthermore, this study strongly supported the literature relating to the role of visual analytic systems in Higher Education. Repeatedly, participants expressed how dashboards and visualizations were integral with helping administrators with less technical skill than their staff better understand the data for decision-making (Mariani, 2016; Williams, 2016). Participants also commented how using multiple dashboards assisted with sharing and collaborating data across institutional departments (Campbell, 2018). Moreover, as data governance and siloed data were generally not viewed as a barrier to sharing or collaborating (Parnell et al, 2018). Some participants even claimed that access to data might be too open but could utilize access controls if they needed to keep other staff from seeing information not relevant to their department (Lamba & Dubey, 2015). Lastly, and probably most meaningful, participants reported that sharing dashboards and visualizations to both administration and across departments ultimately led to more informed and better decision-making for their institution (Seymore, 2019; Williams, 2016).

When considering how to improve data sharing and collaboration across institutional departments, most of the study findings supported the literature. Through the initiative "Achieving the Dream" (ATD), most of what the literature cites as ways to improve data sharing or collaborating in 2-year institutions were implemented to varying degrees. For example, Parnell et al. (2018) suggested devising "evaluation teams", consisting of individual staff members across departments to establish and maintain data governance procedures. While participants generally stated that data governance was not an issue in terms of disseminating data or implementing data mandates (Mathies, 2019), ATD enabled institutions to create "data teams" that provided easier access to data and a better method of sharing and collaborating with student success data concerning at-risk and underserved student populations. In addition, some participants reported that at least one technical staff person from each department served as a member on these data teams, while the IR department would lead and train the team members, in a sense following the advice from Arellano (2017) by acting as an online community that shares common data and software tools. Furthermore, ATD would also provide 2-year institutions with a means to integrate the current existing roles of institutional staff into "prescribed data roles" that related to their department (Díaz, Rowshankish, & Saleh, 2018). Although the degree to which this was accomplished was not clarified in this study.

One aspect of the literature that was not necessarily supported by the study findings was the ability level of analytical managers, or as known is this study, IR Directors, to utilize data systems in comparison to their more technical staff. However, it should be noted that the literature concerning the knowledge gaps between analytical managers and staff came from fields outside of education. Nevertheless, participants frequently indicated that IR Directors were highly knowledgeable with data analytic technology in terms of data analysis and reporting, and some directors were even experienced with data visualization as well as data coding. This was indeed a surprise as most participants did not have such a wide knowledge gap in comparison to the technical staff, which was previously mentioned in the literature as an issue outside of education (Tabesh, Mousavidin, and Hasani, 2019). Perhaps this was due to 2-year institutions having smaller IR departments than their 4-year counterparts, to which it is expected for IR directors to perform multiple roles within their department out of necessity. Moreover, it is possible that there has indeed been a "cultural shift" from the traditional role of the analytical manager in 2-year institutions to a more technically savvy IR director (Williams, Lyytinen, & Boland, 2015).

Recommendations

The following are suggested recommendations based on the thematic findings of this study.

Strengthening Data Governance for Dashboards and Data Visualizations

According to many participants, data visualization has contributed to the improvement of student success in several ways. First, dashboards assist administrators with both understanding and accessing relevant student data with minimal help from IR staff, which can encourage “buy-in” from administrators concerning the value of data-informed decision making. Second, dashboards can provide an impetus for student success initiatives by revealing to institutions the need for improved student outcomes via statistical trends in course outcome analysis or retention and graduation rates. Furthermore, dashboards can assist administrators with monitoring key performance indicators when attempting to improve student outcomes during strategic initiatives. Lastly, dashboards can help identify at-risk and underserved populations that need additional academic support.

Despite the many positives outcomes resulting from the use of dashboards, some participants had reservations concerning the level of access that dashboards allow various institutional staff. For instance, if the access controls for dashboard filters are not confined to only directors or administrators, faculty from one department could potentially access the performance data of another department. Given that state funding is based on student performance, this could lead to conflicts between faculty or departments regarding their relevancy to the institution, an unintentional consequence that administrators would like to avoid.

Beyond the obvious recommendation of simply adjusting the access controls or reconfiguring the software on any given dashboard there are larger issues at hand. First, the perspectives of staff when considering the appropriate level of access to dashboards could vary from person to person. In addition, considering the trend of institutions moving their data to centralized cloud servers there could also be potential for security risks from outside an institution as well. Third, according to some participants in this study, data governance at their institution was very informal, meaning, it usually consisted of verbal agreements between staff or departments concerning the level of access or use of data. Furthermore, these informal agreements were often temporary and restricted to specific data projects or strategic initiatives. Regulating the access to dashboards through some form of data governance operational policy would prevent faculty and other lower-level staff from taking issue with the data of another department, while also ensuring that only IR and administration can access the institutional data in its entirety.

Expanding Predictive Analytics to Further Student Success

Proponents of expanding predictive analytics in this study indicated how it has contributed to the betterment of institutional research regarding student success. “Real-time” analytics have enabled institutional staff to be more proactive with struggling students by identifying them more quickly, versus waiting until the end of a semester to provide interventions. Another participant also alluded to classroom utilization predictive models which inform both student success and operational efficiency by applying course-enrollment patterns along with student demographics and student interest survey data to predict future course enrollments (Larkan-Skinner & Shedd, 2021). These types of predictive models assist advisors concerning at-risk students, as well as facility usage pertaining to classroom space utilization.

Relatedly, enrollment departments, the first aspect of higher education utilizing predictive analytics for administrative purposes, has also benefited from predicting student success outcomes using pre-enrollment high school performance data and interest surveys. Findings from these models also inform advisors and facility usage, as well as enrollment budgetary needs prior to student matriculation. Moreover, institutional administrators have profited by the ability to monitor the KPI's of student performance metrics via dashboards to track their likelihood of state-appropriated funding. Ultimately, this ability alone, it could be argued, leads to a higher demand for the expanded use of predictive analytics in higher education.

Some lesser-known uses for predictive analytics in IR include operational aspects of institutional administration. In addition to enrollment financial predictions, predictive analysis can also determine the likelihoods of budgetary spending for institutional departments. Findings from these analyses can inform training programs to assist departments with managing their budgets. Another operational use of predictive analytics for IR is human resources. Predictive modeling can predict the likelihood of staff turnover as well as retirement preparation (Wyatt, 2019).

The more skeptical participants of this study suggest that those who support the expansion of predictive analytics in IR do not understand the issues surrounding its implementation. For example, some contend that for predictive analytics to be reliable, an institution must systematically collect data for a 2-to-3-year span. This fact could be especially difficult for institutions with smaller enrollment sizes such as community colleges. Any parameter changes made during the data collection phase, such as student population demographics, or how variables are measured and defined, could potentially skew the analysis rendering predictive modeling ineffective. The more skeptical participants also contend there are some aspects of student life which cannot be measured in predictive modeling. These aspects would potentially include any issues that might pertain to the social life of a student, such as traumatic life events, conflicts at home, or a lack of friends at the institution. Lastly, data findings from the predictive analysis might not apply to the context of the institution. A more humorous example of this would be library usage, in which one might conclude that higher usage of the library might lead to better student outcomes unless the library includes a popular coffee shop (Larkan-Skinner & Shedd, 2021**).**

According to the participants of this study, it seemed the most fervent opposition of expanding predictive analytics was related to the issue of privacy or surveillance. This mostly related to utilizing the learning management system (LMS) (e.g. Canvas) of an institution as a means to track and monitor the progress of a student through class assessments and assignments, as well as the interactions with their instructors or other students like blogs or messaging. To optimize the data from the LMS, the data entry by the instructor at the very least must be standardized by how and when the data is entered, and perhaps even made mandatory to ensure the reliability of the predictive modeling by getting all the course or departmental data in its entirety. Other examples of privacy issues with predictive analytics are using data from student services, be it academic or otherwise. For example, the number, frequency, or length of interactions from advising or tutoring sessions could be standardized and introduced into predictive modeling, as well as the utilization of an institution's Wi-Fi or recreational and dining facilities. Policies such as these are sure to receive pushback from some institutional faculty and staff.

As with the first recommendation of this study, any obstacles concerning the expansion of predictive analytics should be mediated with solid data governance. Furthermore, administrators should discuss at-length with institutional staff and be cognizant to include IR staff, to decide what data should be included in their modeling, according to what is appropriate to the individual institution, if at all (Ekowo & Palmer, 2017). Before making any decisions however, administrators should consider how other institutions (Georgia State University, n.d.a.) and third-party consulting organizations (Huron Consulting Group, 2019) have implemented predictive analytics in higher education to understand more fully what would potentially work, or not work, given the situational contexts of their respective institutions.

Due to the many pitfalls, it is understandable why institutions might be slow or even unwilling to expand the use of predictive analytics by utilizing the LMS for student performance data. For those institutions unsure or wary of the potential blowback to what some might view as strict or invasive policies "under the guise" of data governance, there is an alternative to utilizing "true" predictive analytics to assist with improving student success. One participant in this study alluded to this possibility as "using a combination of historical analysis with some current data" (Participant #10). For example, one instance of using a combination of historical and current data is by using high-school academic and demographic enrollment indicators (historical) in conjunction with student performance data and financial aid information (current) to create matriculation and first-year retention probabilities (Troutman & Creusere, 2018).

Data Literacy Training

Exhibiting the ability to both utilize data analytic software as well as interpret the data findings are skill sets readily sought after by IR departments. Possessing these skills simultaneously to some varying degree of competency is what is known as data literacy (Hawkins & Bailey, 2020). Throughout this study, participants often referred to the impact of training that pertained to either one or both skill sets of data literacy. For example, a couple of participants remarked how a reporting software called Argos was underutilized even though it was available to most departments. Both participants speculated that the underutilization of the software was due to a lack of training because its operation required a low-level knowledge of coding to extract the data, which was a skill that most departmental staff did not possess. Regarding data interpretation, one participant remarked that even though software training would always be important, ultimately, the ability to interpret data was a greater need as it was more difficult to train, and the situational needs of each institution are unique.

Conversely, when training needs were met, some participants reported positive experiences. One participant stated how training administrators and academic deans on customized reporting apps helped them replace cumbersome data extraction and reporting software with a tool that is more user-friendly with accessing data for those with less technical skills. Another participant stated how Power BI training assisted administrators with making interpretations from the institutional data on dashboards, such as the KPIs of student data and how they related to state-appropriated funding. Furthermore, during the implementation of "Achieving the Dream", a participant reported that the initiative had undoubtedly enabled the IR staff to better train themselves as well as technical staff from other departments with both utilizing data analytic software and interpreting data findings by identifying knowledge gaps and measuring student success outcomes for underserved student populations.

As technology use becomes more complex in higher education, so will the need for data literate institutional decision-makers like IR directors and administrators. This is particularly true for 2-year institutions with smaller IR departments which depend more heavily on its IR directors to understand both the technical and interpretive nuances of institutional decision-making from data analytic systems. Additionally, when considering the inevitable expansion of predictive analytics in higher education as well as other related advancements of analytical platforms like data visualization software, it is imperative that data literacy training become priority for 2-year institutions. Data literacy training will not only improve the competency of IR directors, but it will also help them bridge knowledge gaps between them and their technical staff as well as administrators. Administrators will in turn, begin to value data more highly, as they understand how data findings can be interpreted and applied to their specific needs of their institution.

Conclusion

The preceding chapter discussed the implications of the findings from this study and offered recommendations pertaining to the improvement of the impact of data analytic systems on institutional decision-making. This chapter began with summarizing the findings from the previous chapter followed by connecting the findings with the current literature.

Subsequently, this chapter made recommendations concerning how to better utilize data analytics to impact institutional decision-making. These recommendations consisted of strengthening data governance for dashboards and data visualizations, expanding predictive analytics to further student success, and data literacy training. Limitations included a lack of generalizability, subjective responses of the participants, and a small sample size restricted to one state in the southeastern United States.

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Appendix

Appendix A: Informed Consent Statement

Perspectives of IR Professionals Regarding the Impact of Data Analytic Systems on Institutional Decision- Making.

You are invited to participate in a research study conducted by Richard Parlier at the University of Tennessee, Knoxville. You are being invited because of you are a professional of institutional research (IR), or of a similar institutional department at a two-year institution. Participation in this research study is completely voluntary. Only participate if you both agree that you completely understand and want to contribute your perspectives to this study. This form contains information that will help you decide if you want to participate in this research study. Please read this form carefully, if you have any questions please contact the principal investigator. Contact information is listed at the bottom of the form.

Purpose

The purpose of this interview will provide feedback for understanding the perspectives of IR professionals in 2-year institutions regarding the impact of data-analytic systems on institutional decision-making. Feedback will also potentially help those institutions with data analytical needs. This includes how institutional decision-making is impacted from:

- understanding the roles of IR professionals in 2-year institutions with analyzing and interpreting data analytical findings.
- how IR professionals in 2-year institutions such as Chief Data Officers (CDO's), IR directors, IR associate directors, IR analysts, IR data scientists, other technical staff collaborate on data analytical findings with one another in relation to their differing skills sets.
- understanding the general attitude of 2-year institutions towards data governance, policies, processes, relevancy, and conduciveness with sharing data and collaborating on data analytical projects with staff in other departments outside of institutional research.

Participation

Participation in this study will involve a 30 - 60 minute interview regarding your perspectives of the impact of data-analytic systems on institutional decision-making. Participation in this study also involves being audio and video recorded through online Zoom software.

Risks and discomforts

If you participate in this study, findings from your interview could be published in a dissertation report and may be presented at national scholarly conferences. Due to the small sample size, participants could be identified from the information they give during their interview, such as their role within their IR department, or their perspective of their institutional culture. In addition, using Zoom technology or Rev.com to transcribe interviews will pose minor security risks related to the participant interviews being uploaded and transcribed on a centralized cloud data center. There are no other risks, costs, or discomforts associated with this research that we know of beyond what I have mentioned.

Confidentiality
To minimize these potential risks, your name and the name of your institution will not be mentioned in the final report or future presentations to protect your identity. Additionally, specific participant names and their institutional names will be cleaned in final transcript of the interviews. Any demographic or background information will be reported in aggregate. This interview will be recorded and stored on confidential, password protected software to ensure the accuracy and privacy of the information you will provide. The audio and video recording will be destroyed after the recording has been transcribed and identifying information will be deleted.

When using Zoom technology or staff from rev.com to transcribe interviews, participant data will be synced over an encrypted connection and stored on a secure password protected data cloud that has both physical and electronic security. Zoom does not sell or share data with anybody (except as necessary to respond to lawful requests). Rev.com follows all best practices regarding study participant confidentiality. All staff transcriptionists will be required to sign confidentiality agreements. There are no other risks, costs, or discomforts associated with this research that we know of beyond what I have mentioned.

Any information you provide will be kept strictly confidential. Your identifiable information will be removed from any transcription, report, presentation, or any other information that is produced as a result of this study. If you have any questions during this interview do not hesitate to ask the researcher.

Future Research
Your information may be used for future research studies or shared with other researchers for use in future studies without obtaining additional informed consent from you. Should this occur, all of your identifiable information will be removed before any future use or sharing with other researchers.

Contact Information
If you have any questions about this research, please contact, Richard Parlier (tparlier@vols.utk.edu) or Dr. Gary Skolits (gskolits@utk.edu). If you have any questions about your rights as a research participant, please contact the Institutional Review Board (IRB) of the University of Tennessee, Knoxville, at utkirb@utk.edu or 865-974-7697. You may also contact the IRB with any problems, complaints or concerns you have about a research study.

What will happen if I say “No, I do not want to be in this research study”?
It is completely up to you to decide to be in this research study. Even if you decide to be part of the study now, you may change your mind at any time by informing Richard Parlier via email. You will not lose any services, benefits, or rights you would normally have if you choose not to volunteer, or if you change your mind and stop being in the study later. If at any time you

decide not to participate in this research study, even while being interviewed, you will not be penalized in anyway. Your identifying information and interview responses will not be included in the study.

Consent

Your participation in this research study includes allowing Richard Parlier to use your information for research purposes. By marking an "X" in the box next to the statement "I agree to be included in this study" you indicate that you have read the above information and understand that you are agreeing to participate in this study. In addition, your participation in this research study also includes allowing Richard Parlier to use video/audio recordings for research purposes. By marking an "X" in the boxes next to these statements below you agree to be audio and/or video recorded for this study. You may keep a copy of this consent information for future reference. If you do not want to be in this study, you do not need to do anything else.

☐ I agree to be included in this study.
☐ I agree to be audio recorded in this study.
☐ I agree to be video recorded in this study.

Appendix B: IR Professional Interview Protocol

Perspectives of IR Professionals Regarding the Impact of Data Analytic Systems on Institutional Decision- Making.

Introduction:

Interviewer: Good afternoon and welcome! My name is Richard Parlier, and I am a PhD student in Educational Psychology at the University of Tennessee – Knoxville. Thank you for taking the time to speak with me today on your experiences as an IR professional. The purpose of this interview is to learn more about your perspectives and experiences as an IR professional regarding the impact of data analytical systems on institutional decision-making. The interview will only take about 30-60 minutes to complete.

Your feedback will provide information regarding the perspectives of IR professionals in 2-year institutions and potentially help those institutions with data analytical needs. This includes how institutional decision-making is impacted from:

- understanding the roles of IR professionals in 2-year institutions with analyzing and interpreting data analytical findings.
- how IR professionals in 2-year institutions such as Chief Data Officers (CDO's), IR directors, IR associate directors, IR analysts, IR data scientists, other technical staff collaborate on data analytical findings with one another in relation to their differing skills sets.
- understanding the general attitude of 2-year institutions towards policies, processes, relevancy, and conduciveness with sharing data and collaborating on data analytical projects with staff in other departments outside of institutional research.

Any information you provide us today will be kept strictly confidential. Your identifiable information will be removed from any transcription, report, presentation, or any other information that is produced as a result of this study. If you have any questions during this interview do not hesitate to ask me.

This interview will be recorded and will be stored on confidential and password protected software to ensure the accuracy and privacy of the information you will provide. The audio and video recording will be destroyed after the recording has been transcribed and identifying information will be deleted. Any questions?

Is this okay that I record this interview? (Say "yes" or nod)

----------------------------Start Recording--

Interview Protocol

1. As an IR professional, how would describe your daily work duties?
    a. Do your work duties involve: analyzing data findings, interpreting data findings, sharing data findings with other departments, or collaborating on data projects with other departments?
    b. Do your work duties involve using: institutional business metrics for funding/finances, key performance indicators (KPI's) for student success or curriculum/instruction?
2. What is the current data analytical (information) system your IR department uses for institutional decision-making?
    a. In general, how would you describe the impact of your current data analytical system on institutional decision-making?
    b. In general, how would you describe the data analytical system in terms of system quality? (e.g. ease-of use, interactive)
3. How would you describe the quality of communication with IR professionals that have differing roles from your own during the decision-making process?
    a. Is your/their role mainly interpretive and functional? (i.e., implementing data analytic findings to improve institutional policies and processes)
    b. Is your/their role mainly analytical and technical? (i.e., analyzing statistical findings; coding)
4. How would you **describe the impact of the current data governance policies** from your institution when sharing or collaborating on data analytic findings for cross-departmental projects?
    a. Are there barriers to sharing findings across departments?
    b. Are there barriers to collaborating on projects across departments?
5. How would you describe the **general attitude of your institution when sharing and collaborating** on data analytic findings for cross-departmental projects?
    a. Does the general attitude of your administration present barriers to sharing/collaborating?
    b. Does the general attitude of other departments outside of institutional research present barriers to sharing/collaborating?
6. How have you **overcome these governance or attitudinal barriers** while performing your duties as an IR professional?
    a. When sharing data with other departments?
    b. When collaborating on projects with other departments?
7. How do you utilize visual analytical systems for institutional decision-making?
    a. How do you utilize visual analytics to interpret data analysis or when sharing data and collaborating with other departments for institutional decision-making? (e.g. dashboards, early-warning alerts, centralized server)
    b. How do you utilize visual analytics to comply with data governance? (e.g. access settings, automized editing accuracy or compliance mechanisms)
8. Are there any other issues that have not been mentioned in the prior questions which effect you as an IR professional regarding the utilization of data analytical systems on institutional decision-making?

Interviewer: That is all the questions I have for you today. Do you have anything you would like to add or any questions for me?

Thank you again for your participation today. After the interview has been transcribed and coded for analysis, a copy of the final transcript will be provided to you for member checking. Member checking is a process to ensure that I have accurately captured and interpreted your views expressed during our interview. At that time, if there are any statements that you would not like to be used, you can let me know and I will redact them from further analysis.

Thank you again for your participation today.

Appnedix C: Participant Recruitment E-mail

Dear, [insert name]

My name is Richard Parlier and I am a doctoral candidate from the Evaluation, Statistics, and Measurement program in the Department of Educational Psychology and Counseling at the University of Tennessee, Knoxville. I am inviting you to participate in my research study regarding the perspectives of IR professionals on the impact of data analytics with institutional decision making. In addition, I have sent this email to you because you are a professional of institutional research (IR), or of a similar institutional department, at a two-year institution. I obtained your contact information from (IR-related association and IR-related association website address/or personal contact name).

As an IR professional, if any of the following job duties pertain to you, you are eligible for this study:

- Utilize data analytic systems for institutional decision-making as a Chief Data Officer (CDO), IR director, IR associate director, IR analyst, IR data scientist, or other technical staff.
- Analyze, interpret, share, or collaborate on data analytic findings for institutional decision-making.
- Participate on data analytic projects for institutional decision-making that includes other departments outside of the institutional research department (or of a similar institutional department).

Participation in this study will involve an interview that will only take 30-60 minutes to complete. Your interview will take place via Zoom and will be audio and video recorded. However, any information you provide will be collected and transcribed solely for the use of this research project. Furthermore, your name, and the name of your institution will not be mentioned from any transcription, report, presentation, or any other information that is produced as a result of this study.

I am currently scheduling interviews with IR professionals to gather their feedback. If you choose to participate, please respond with your consent from the form attached to this email and I will email you an invite via Doodle to schedule a time for your interview. In addition, please feel free to forward my name and contact information to any IR professionals who might be interested in providing feedback.

If you have any questions about this research project, please feel free to contact Richard Parlier (tparlier@vols.utk.edu) or Dr. Gary Skolits (gskolits@utk.edu). Questions or concerns about your rights as a research participant should be directed to The Chairperson, University of Tennessee-Knoxville Institutional Review Board (irbchair@utk.edu).

Thank you for your consideration! Please keep this letter for your records.

Sincerely,

Richard Parlier, MS
Doctoral Candidate
Evaluation, Statistics, and Measurement
University of Tennessee, Knoxville
Email: tparlier@vols.utk.edu
Phone: 770-262-3099

Follow Up E-mail

Dear,

You are receiving this e-mail because of your connection to, or are a professional of, institutional research (IR) (or similarly named department) at (institution name). If your job duties consist of one of the following you are eligible to participate in this study:

- Utilizing data analytic systems for institutional decision- making
- Analyzing/interpreting/sharing/collaborating on data analytic findings for institutional decision-making
- Participating on cross-departmental projects by utilizing data analytic systems for institutional decision-making with multiple departments.

As a PhD student in Educational Psychology, I am conducting my dissertation on the perspectives of IR professionals in 2-year institutions regarding the impact of data analytical systems with institutional decision-making. Your feedback will provide information regarding the perspectives of IR professionals and potentially help those institutions with data analytical needs. This includes how institutional decision-making is impacted from:

- understanding the roles of IR professionals in 2-year institutions with analyzing and interpreting data analytical findings.
- how IR professionals in 2-year institutions such as Chief Data Officers (CDO's), IR directors, IR associate directors, IR analysts, IR data scientists, other technical staff collaborate on data analytical findings with one another in relation to their differing skills sets.
- understanding the general attitude of 2-year institutions towards policies, processes, relevancy, and conduciveness with sharing data and collaborating on data analytical projects with staff in other departments outside of institutional research.

Attached are interview dates and times along with relevant materials for participant invitations. Please forward this information to any possible participants who would be interested in providing feedback on their experiences.

I am currently scheduling interviews with IR professionals to gather their feedback. Please feel free to forward my name and contact information to any IR professionals who might be interested in providing feedback.

Finally, if you would like to provide feedback on your experiences, please respond to this e-mail with available dates and times for interviews.

All interviews will be conducted via Zoom technology. All interviews will follow IRB approved protocols.

Please feel free to contact me with any questions or for additional information.

Sincerely,

Richard Parlier, MS
Doctoral Candidate
Evaluation, Statistics, and Measurement
University of Tennessee, Knoxville
Email: tparlier@vols.utk.edu
Phone: 770-262-3099

Vita

Richard Parlier is originally from Alpharetta, Georgia. Following high school, he attended the University of Georgia and received a Bachelor of Science degree in Biology. Four years later, he received a Master of Science degree in Professional Counseling from Georgia State University. After working 12 years in both private and public sectors, Richard attended the University of Tennessee, Knoxville to pursue a Doctor of Philosophy degree in Educational Psychology and Research with a concentration in Evaluation, Statistics, and Measurement. Upon graduation, he will search for fulltime positions in either non-profit educational consulting firms or evaluation centers. Richard is extremely thankful for the support he received from his family, friends, and colleagues as he embarks on his new career.