2021

Higher Education Administrator Perceptions and Experiences in Predicting and Tracking Retention

Judee Lynn Mulhollen
Walden University

Walden University

College of Education

This is to certify that the doctoral study by

Judee Mulhollen

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

and that any and all revisions required by

the review committee have been made.

Review Committee

Dr. Steven Wells, Committee Chairperson, Education Faculty

Dr. Jamie Patterson, Committee Member, Education Faculty

Dr. Elsa Gonzalez, University Reviewer, Education Faculty

Chief Academic Officer and Provost

Sue Subocz, Ph.D.

Walden University

2021

Abstract

Higher Education Administrator Perceptions and Experiences in Predicting and Tracking Retention

by

Judee Mulhollen

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Education

Walden University

October, 2021

Abstract

The problem guiding this study is that many administrators of 4-year colleges do not have efficacious application practices in terms of tracking and predicting student retention. This basic qualitative study was conducted to explore perceptions and experiences of administrators of U.S. 4-year colleges regarding tracking and predicting retention. The conceptual framework was based upon the Attaran analytics model and the three V model. Both involve decision-making perspectives seen frequently in higher education. The research question guided exploration of the perceptions and experiences of higher education administrators of 4-year U.S. colleges in terms of the application of student data for tracking and predicting retention. A basic qualitative design was used with a criteria-based sample consisting of 10 U.S. college administrators who had student data identification or retention initiatives among their responsibilities. Data were collected through semistructured interviews, and qualitative analysis was conducted using a priori, open, and selective coding. Major themes included a need in higher education for common language and processes for data mining, desiloing data, and informed decision-making. This study will contribute to positive social change by increasing higher education administrators' understanding of efficacious practices to predict retention that ultimately influence college student success and institutional revenue.

Higher Education Administrator Perceptions and Experiences in Predicting and Tracking Retention

by

Judee L. Mulhollen

M Ed, Ashland University, 2003

BBS, University of North Dakota, 1996

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Education

Walden University

October, 2021

Dedication

To all of the women out there who have been made to feel less than or not worthy of having dreams or personal goals. Your strength is inside you and nowhere else, find it, and be free of judgement and those who wish to steal joy. My hope is that my three daughters can be inspired to see their mom/step-mom, come from a family of hard working Irish folk that never dared to dream about going to college and removing barriers to their success. They were better than I in many ways and have been my silent partners these past six years, and I will forever be grateful to them for laying the groundwork that I stand upon.

Acknowledgments

My grandfather. At a young age he instilled in me my value and my place as a girl in this world. He always said he would pick me any day over most boys my age because I worked so hard until the job was done, and done right, and he said that a price cannot be put on result of hard work. As always, he was right. I miss him every day, but he is forever with me.

I would be remiss if I did not thank my beautiful husband and children for their love, encouragement, support, and patience. It is amazing how the past six years went so fast and yet so slow. But without my Pete, Noah, Maddy, Caroline, Greyson, Hannah, and beautiful grandson, Noah, I would not have been able to withstand the stress and pressure this adventure consistently spun. Thank you all and you are sweet, intelligent, and strong, each in your own right.

Last, and certainly not least, are the four professionals that were my biggest advocates and most appreciated Walden team. I cannot even begin to thank you enough. Dr. Hamilton, you and I are the last ones standing. We started this together six years ago and here we are. I do not have to mention all the strife and stress that befell my journey, because you were there. You never gave up, lost your patience, or stopped believing in me and my dissertation trek. And because of that I have had the absolute pleasure to work with and be supported by Dr. Steve Wells and Dr. Jamie Patterson as my committee.

Dr. Wells and Dr. Patterson, I know heavy handed words can seem insincere, so I do not want to create a string of words that seem ingenuine. But I have been forever changed by the sharing of your knowledge, your composure during times of great stress, and your witty humor in an effort to lighten the mood and bring me back down to earth.

Thank you so much. Dr. Gonzalez, my URR, I extend my appreciation for your guidance and support throughout this challenging and iterative process. And Dennison Peters, you are a gem in a field of stone. You cared when no one else did, you found resources when others said there were none, and supported me most when I felt alone in this journey. Thank you, from the bottom of my heart.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction to the Study

The topic addressed in this study is the application of student data by administrators of 4-year colleges in tracking and predicting retention. Student data are derived from student behavior characteristics and attributes that are tracked during their academic pursuits in higher education. There is a limited number of studies about higher education application of student data used for tracking and predicting retention. This gap in the literature affects the information that is needed to address the gap in practice about processes required to scaffold tracking and predict retention in higher education. A strong sense of urgency is needed to reaffirm administrators of higher education and their commitment to using chosen student data to make better strategic decisions, especially as it relates to student retention. Brown (2019) said that educational leaders should be advancing using predictive analytics to channel new tools for the success of institutions and student retention at their chosen university. This study was conducted to address a gap in literature by informing practices of administrators at 4-year colleges about processes needed for efficacious student data applications to track and predict retention in higher education.

This study will contribute to positive social change by increasing higher education administrators' understanding of best practices in applying student data targeted to predict and track retention, ultimately influencing student success and institutional revenue. This can prove to be valuable and lead to institutional sustainability. An efficacious process for predicting and tracking retention is an asset in higher education as it allows innovative recruitment and increases overall efficiency and cost containment when students are retained. Neelakantan (2019) said the understanding in higher education of student data for variable identification used for institutional advancement initiative fuels well-organized processes that allow staff to work smart for increased time management. This can underpin confidence in the adoption of better decision-making processes as it relates to student data. Use of policies and procedures that enable data managers to make informed decisions based on evidence rather than intuition as this aligns with best practices shown in suggested data analysis processes (Sivarajah, et al., 2017; Schneider & Preckel, 2017) that are now expected by higher education accrediting bodies, such as The Higher Learning Commission.

I explore this topic in this chapter. I begin with the study's background with a brief description of the focus and scope regarding student data application for retention tracking in higher education. The problem, purpose, and research question are presented along with the conceptual framework. The nature of this study and significance of other research is addressed along with a brief discussion of the study's assumptions, scope, and delimitations, followed by a summary of this chapter.

Background

This study involves perceptions and experiences of administrators of 4-year U.S. colleges regarding identifying student data for tracking and predicting retention. This study's scope is appropriate to interpret experiences and perceptions of administrators of 4-year colleges regarding their understanding of the phenomenon that will inform best practices in terms of the application of student data and retention. The scope of data collection was not limited by geographical location since these interviews were conducted in a virtual format as well as face-to-face. Data were collected from 12 administrators from U.S. 4-year colleges who were recruited using criteria-based sampling.

This study can bridge the gap in literature regarding the application of student data to track and predict student retention in higher education. Wilderotter (2020) said the lack of faculty and administrator understanding of one's student population and their attributes can prevent selection of variables that measure retention in a meaningful way. Wilderotter also said critical planning for retention in higher education involves understanding student enrollment trends and what influences those trends for student decision-making when choosing a college. Additional research is needed to help higher education administrators identify predictive student data for retention.

The current study is needed because it will benefit higher educational institutions and the data administrators that plan for student retention tracking initiatives. Neelakantan (2019) said returns on investment for intentional planning for student retention variables outweighs costs. Avella et al. (2016) said that many higher education administrators are currently unable to communicate the linkage between student data, identifying variables for tracking student retention. Huda et al. (2018) said that higher education administrator knowledge of data mining processes identified for retention efforts drive best practices for tracking and predicting college student retention and institutional stability through increased funding. This study is needed to further address gaps in research that influence the gap in practice that is needed for administrators in higher education to identify and apply student data for higher education internal research of retention initiatives in 4-year U.S. colleges.

Problem Statement

The problem guiding this study is that many administrators of 4-year colleges do not have efficacious application practices for student data in terms of tracking and predicting student retention. Wang (2017) said that despite abundant data availability, higher education administrators have a limited understanding of student behavior characteristics that are needed for analyzing and selecting appropriate variables for overall institutional research. According to Wang, this has a negative effect on data management practices and student success outcomes, in that the limited understanding of the data process itself is a hindrance to reliable outcomes.

This study builds upon previous research findings about processes and policies for identifying student data that can be applied as variables for data analysis as well as using analytics for tracking and predicting retention in higher education. Sass et al. (2018) said data mining practices are typically siloed and fluid within institutions and are characterized by a lack of planning as it relates to internal retention efforts. Huda et al. (2018) said higher education administrators continue to struggle without guidance on data management practices for selecting variables from raw data to track and predict student retention. Further, a lack of knowledge exists among many data administrators in higher education who lack appropriate data mining policies and processes to drive student support practices. This lack of data knowledge and practice prevents the successful function of innovative business intelligence in higher education in terms of retention for revenue stability (Elhassan et al., 2018).

Purpose of the Study

The purpose of this basic qualitative study is to explore perceptions and experiences of administrators of 4-year colleges in terms of their application of student data for tracking and predicting retention. The basic qualitative methodology was used in this study to generate an increased understanding of this phenomenon. Increased understanding is needed for higher education administrators for the process of selection of student data and how they are applied to tracking and predicting retention. This understanding in higher education for analyzing and selecting data is important because student attributes that feed into data selection processes may change depending upon trends influencing higher education (Arensdorf & Naylor-Tincknell, 2016). Matsebula and Mnkandla (2017) said changing trends can further affect retention tracking because of the needed reevaluation of targeted student data.

Research Question

The research question that guided this study is:

RQ1: What are the perceptions and experiences of higher education administrators of 4-year colleges in terms of the application of student data targeted for tracking and predicting retention?

Conceptual Framework

The process of understanding and interpreting raw data is not reduced to a predetermined method, but it occurs during the interpretive process itself (Mills et al., 2010). The primary function of the conceptual framework is to provide a clear and concise mechanism for interpretation and understanding in a qualitative study (Barbour, 2014). These two models were specifically chosen to underpin this study because they provide the basic knowledge and defined terms that make up data components of any retention initiative. Part of gauging the higher education perceptions and experiences in this study will rely upon their basic knowledge of data mining terms. The conceptual framework models of Attarran et al. (2018) and Gandomi and Haider (2015) constitute the data mining and analysis structure needed to inform these perceptions and experiences. A more detailed analysis of this will be provided in Chapter 2.

The conceptual framework for this study is informed by a model of analytics by Attaran et al. and the three V construct by Gandomi and Haider. Given the strong knowledge base needed from participants regarding data mining protocol and language, these are appropriate conceptual framework models for this study. A more detailed analysis of this dual lens conceptual framework will be provided in Chapter 2.

The Attaran et al. model takes a three-pronged approach to analytics: descriptive, predictive, and prescriptive. These three approaches involve decision-making perspectives seen most frequently in higher education. First, descriptive analytics allows for a rearview mirror approach to describe data variables chosen that will assist in choosing a path forward given what has or has not been successful results in the past. This means that previous data outcomes can be reviewed for historical perspectives and provide a course forward given past behavior collected from data and whether this behavior is still wanted or not (Attaran et al., 2018). The second prong of this three-pronged approach is predictive analytics. This particular perspective considers historical data as well as current data mining results. It is useful in identifying potential risks as well as opportunities for growth and development with appropriately identified variables that show patterns of data that serve to predict future behavior of the group being studied and analyzed with targeted data points. Finally, the prescriptive analytics tool of this model allows decision-makers a simulation process to optimize an action being considered in policy or practice. This is a valuable approach and goes beyond descriptive and predictive analytics by helping decision-makers decide what happens next and why this course may be best given the data patterns from the group being studied or analyzed. Kivunja and Kuyini (2017) said that any study based upon basic data mining skills for the understanding of analysis results and its application in higher education should have a data mining model as the basis of policy and practice, such as Attaran, et al. and Gandomi and Haider, that provide the dual lens of the conceptual framework of this study.

The second model supporting this study is the three-V construct by Gandomi and Haider. The three Vs stand for: velocity, variety, and volume. Velocity refers to the speed at which data is constantly uploading into a data system. Variety is diversity of data such as gender, race, socio-economic status, GPA, and credit ration score (Gandomi & Haider, 2015, p. 138). Volume refers to amount of data, given the size of the institution and number of goals or targets being measured. The three-V model targets raw and unstructured data that compose 95% of data analytics in higher education (Mah, 2016), as well as types of data that higher education administrators and stakeholders consider during their decision-making processes (Chaurasia & Rosin, 2017). Baer and Norris (2016) said higher education administrators cannot begin to understand data analytics and its application without understanding the three V construct.

Exploring perceptions and experiences of administrators of 4-year colleges regarding their application of student data for tracking and predicting retention requires basic knowledge of data mining principles such as those supporting this study in the conceptual framework. Analysis and interpretation are essential to all qualitative inquiries (Silverman, 2016). During analysis, certain characteristics became more important than others and meaningful data from participants were driven by the RQ during this analysis. Further, data analysis was guided by the conceptual framework. It would not be possible to answer the RQ without these models informing the basic participant knowledge necessary to scaffold post analysis .

The conceptual framework guides research components of the study. With understanding of the two models, I created semistructured interview questions. Use of priori codes is frequently referred to as a deductive or beforehand form of analysis, while building codes during analysis is inductive (Castillo-Montoya, 2016). I used priori codes as part of the data analysis procedures. More detail regarding the chosen conceptual frameworks and their alignment with this study is in Chapter 2.

Nature of the Study

I used a basic qualitative design to explore the perceptions and experiences of administrators in 4-year colleges about identifying and applying student variables for tracking and predicting retention. Basic qualitative research is used to examine natural circumstances in which individuals' function, as the objective is to provide a practical understanding of real-world problems (Korstjen & Moser, 2018). Basic qualitative design is an appropriate choice for this study because this design is used to advance knowledge and investigate an academic phenomenon (Given, 2008). I investigated the processes in place for applying student variables in retention, and the perceptions and experiences of administrators using these practices. Another rationale for choosing the basic qualitative design is to address contextual experiences of interest. Patton (2015) said the qualitative inquiry is the chosen method for analyzing people's perceptions and experiences within the context to be understood. Accordingly, I analyzed perceptions and experiences of college administrators.

This design was chosen as opposed to the case study. This is because in the case study design, a researcher is focusing on the concrete, contextual, in-depth knowledge about a specific real-world issue that allows a researcher explore the key characteristics, meanings, and implications of the case (Lichtman, 2020). There is not enough literature on the topic of this study to inform practice in regards to answering the RQ. Because of this reason, the researcher found it necessary to have the open design approach that the basic qualitative study design provides.

The basic qualitative study, sometime called generic, general, or interpretive qualitative designs typically derives from practical issues in the social sciences which provide the context for qualitative semistructured interviews. Data were collected via semistructured interviews by phone or virtual format from administrators at 4-year U.S. colleges who have responsibility for the identification of student data for retention efforts. Number of participants depended upon what was required to reach data saturation. Saturation is achieved when the researcher begins to hear the same comments repeatedly from participants, and no further interviewing is necessary (Saunders et al., 2017).

During data analysis, validity involves obtaining rigor through using techniques of verification such as inductive and deductive coding (Spiers et al., 2018. This approach has two advantages. First, by using a priori codes or deductive coding, I can ask participants questions that relate to their own thoughts and experiences that can help establish rapport as well as gather data. Codes were selected and categorized using NVivo 12 software to ultimately deduct data down to the three major themes. Further discussion of the basic qualitative study design appears in Chapter 3.

Definitions

Terms that need clarification are discussed briefly here.

Some terms that may need clarification will be discussed briefly here.

Data Mining: This is a general term used frequently when discussing the process for identifying variables for research. Specifically defined as the practice of analyzing large databases in order to generate new information (Slater et al., 2017).

Retention: Because this is a common termed heard in both business and education it is important to have the correct working definition. For this study, student retention in higher education is defined as the identified student attributes applied as variables in tracking retention and success of students in higher education from term to term until completion (Alsharari & Alshurideh, 2020).

Student Data: Mentioned throughout this study as part of the key concepts are defined as those student data or characteristics deemed statistically significant for use as variables in tracking a data target (Elegendy & Elragal, 2016).

I assumed that participants shared honest and accurate accounts of their perceptions and experiences when applying student data for tracking and predicting retention. It was further assumed that during the participant selection process, participants accurately portrayed their job titles and responsibilities. This is necessary for internal and external validity of the study. This is also important in terms of answering the RQ and relating this knowledge through semistructured interview questions. Magaldi and Berler (2018) said semistructured interviews are only as strong as identified participants' knowledge base related to the focal topic. These assumptions were necessary for this study to build the research question and semi-structured inquiries for participant interviews.

Scope and Delimitations

The scope of this study includes administrators of 4-year, U.S. colleges who are responsible for student variable applications for tracking and predicting student retention. This study was delimited to 4-year colleges to be specific to higher education administrators without being too narrow (Lichtman, 2017; Patton, 2015). This study was also delimited to only U.S. colleges. Data collection only within the United States can minimize efforts for saturation during the COVID-19 crisis that may influence the participation recruitment process (Bradley et al., 2020). Finlay (2013) stated that in qualitative study, careful thought for participant selection must be done with the essential belief that you look for variety in people to describe, explore, or explain phenomena in real-world contexts. Merriam and Tisdell (2015), and Finlay (2013), stated that researchers and readers can then make connections from the data outcomes. When these reflections are applied to qualitative practices, this is called transferability (Barbour, 2014; Finlay, 2013; Given, 2008; Lichtman, 2017; Merriam & Tisdell, 2015).

Limitations

Bias may reduce credibility, and researchers must control for bias during tool development, sampling, and data interpretation. Researchers should also be aware of personal thoughts, beliefs, values, and opinions so they do not negatively impact their study (Creswell & Poth, 2019). I am a retention and completion director in higher education, and knowledge and responsibilities I have that relate to the focus of this study can cause bias. I minimized my bias by being cognizant of any influence my background may have on the study. Potential weaknesses in the study can influence trustworthiness of the final analysis if not kept in check. I reflected on and attempted to prevent biased activity. I avoided snowball sampling, which could have resulted in too many like-minded participants. I also used a reflexivity journal and restricted myself to the research method process detailed in Chapter 3.

Significance

Findings of this study involve a gap in the literature that is needed to inform practice related to higher education administrators' application of student data in predictive analytics for tracking retention. Hadwater et al. (2019) said that the future foundation of student retention in higher education will involve policies that informs analytics practice to save time, money, and human capital. The findings of this study provide a deeper understanding of processes for identifying student data in predicting and tracking retention. This, in turn, will benefit higher education administrator practice by helping to close the gap in literature (Hadwater et al., 2019). According to Rubel and Jones (2017), to achieve best practices for retention analytics, insight into student attributes and behavioral characteristics must be applied during the identification of student data.

Increased understanding needed for higher education administrators on appropriate student data in predicting retention initiatives can positively influence social change. The intended audiences for this study are higher education decision makers and internal research teams that guide analytics interpretation. This can be done both in higher education and on an individual basis by administrators. Predictive and preventive analytics mining can bolster retention and completion (Chaurasia et al., 2018). Also, improved analytics can promote more efficient use of human capital while increasing revenue (Elhassan Ali & Klett, 2018). This can influence higher education practices to yield improved institutional stability and inform efforts to reduce siloed data ownership pools that impede progress (Nimmagadda & Rudra, 2017).

Summary

This chapter included an overview of this study of administrators of 4-year U.S. colleges and their application of identified student data in predicting and tracking retention. Further, administrators’ experiences and perceptions of student data identified as targets in predicting retention through semi-structured interview questions are grounded in the conceptual framework models of Attaran, et al. (2018) model of analytics and Gandomi and Haider (2015) three-V construct. Limitations were discussed that highlighted participants' lack of knowledge and experience that may influence recruitment and data outcomes as well as researcher limitations given my current job title and responsibilities involving institutional retention. Participants were 10 administrators from eight 4-year U.S colleges . I focused on describing social change implications relating to improved understanding of higher education administrators with data tracking responsibilities in predicting retention, which can positively influence student success and institutional stability by increasing revenue. Chapter 2 contains information regarding the conceptual framework along with a review of current literature.

Chapter 2: Literature Review

The problem guiding this study is that many administrators in 4-year colleges do not have efficacious application practices in place for student data in terms of tracking and predicting student retention. Therefore, the purpose of this basic qualitative study is to explore perceptions and experiences of 4-year college administrators regarding their student data application processes for tracking and predicting retention. Problems with tracking retention arise in higher education without defined processes for applying student characteristics that are specific to data tracked for students who persist in school (Elhassan & Klett, 2018; Mahroeian et al., 2017).. Important components of successful tracking and predicting of retention initiatives in higher education include attitudes and perceptions of administrators who have the responsibility for pertinent use in defining and applying student data (Alsharari & Alshurideh, 2020)

In this chapter, research relevant to this study is reviewed. Literature search strategies and databases used for this research are discussed. I used Stark and Stotler's model of analytics and Gandomi and Haider's three-V construct to address key concepts in this study. Key concepts addressed through this literature review include defining retention in higher education, applying and identifying student data for institutional research, tracking and predicting retention in higher education, and barriers to data mining. These are followed by chapter conclusions and a summary.

Literature Search Strategy

Databases used during the research process for finding literature were: SAGE Journals, ERIC, , EBSCOHost, PROQUEST, PsycINFO, Academic Search Premier, and ProQuest Central. Walden University's Thoreau Library portal and Google Scholar were also used to identify articles not obtained through databases. Key words used were: *analytics in higher education*, *higher education administration decision-making tools*, *higher education administration perceptions of student data applied in retention*, *tracking and predicting retention in higher education*, *Gandomi and Haider three-V construct in higher education*, *Attaran, Stark, and Stotler analytics model in higher education*, *student attributes identified as variables in tracking or predicting retention*, *qualitative study in higher education retention*, *student data in retention*, *how student data application influences student retention tracking*, *higher education student retention*, *retention analytics in higher education*, and *students who retain in higher education.* These key terms were used independently and in combination, and led to four major themes: defining retention in higher education, applying and identifying student data for institutional research, tracking and predicting retention in higher education, and barriers to data mining. There are 60 total sources in the literature review, 41 (68%) of which were published between 2017 and 2021 (see Table 1).

Table 1

Sources in the Literature Review

Source Type	Last 5 Years	Older than 5 Years	Total
Peer Reviewed	40	14	54
Seminal	1	5	7
		Total Sources	60

Conceptual Framework

The conceptual frameworks for this study were the model of analytics and three V construct. Both have origins in general data mining best practices (Baker & Siemens, 2014). Baker and Siemens (2014) said accuracy of education data mining (EDM) metrics is important, as they can determine the relevance of educational experiences to students. Heiner et al. (2007) said the model of analytics establishes processes and tools needed in any data mining effort to operationalize decision-making in order to synchronize data for planned improvement in policy and practice.

Model of Analytics

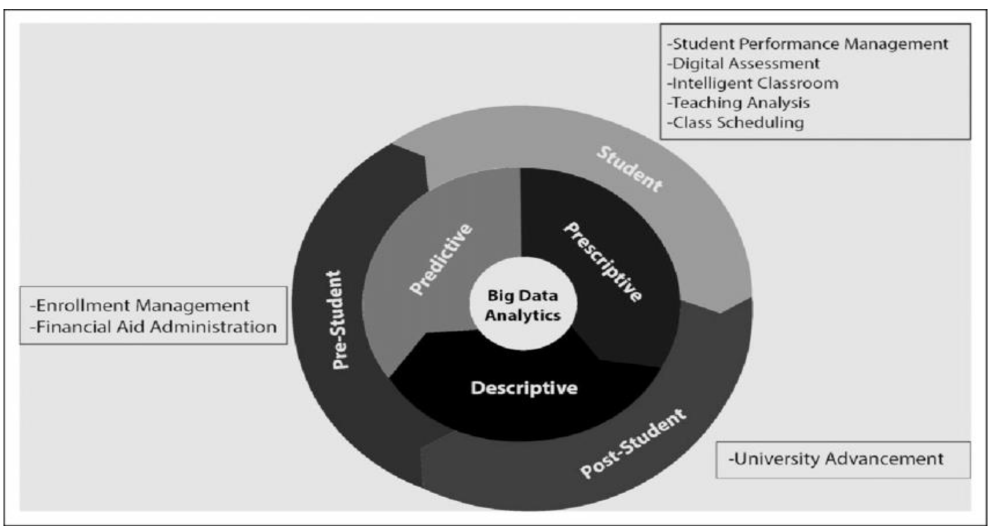
The model of analytics involves a three-pronged approach to analytics: prescriptive, predictive, and descriptive. These address the decision-making perspectives seen most frequently in business and education (Williamson, 2017). Attaran et al. (2018)

said once big data are broken down, these smaller pieces of prescriptive, predictive, and descriptive data allow decision-makers to see patterns and trends from past data outcomes.

Descriptive analytics allow for a knowledge-based approach to deciding future policies and procedures (Attaran et al., 2018). Predictive analytics involves historical data as well as current data mining results. It is useful in identifying potential risks and opportunities for growth and development. The prescriptive analytics approach allows data simulations to optimize an action being considered. Attaran, et al. stated that this is the most valuable approach and goes beyond descriptive and predictive analytics by allowing decision-makers to decide what happens next.

Figure 1

Record-Shape Visual



Three V Construct

. The three Vs of the three V construct are velocity, variety, and volume (Gandomi & Haider, 2015). The speed (velocity) at which student data are available will also include a assortment of data points and diversity of experiences (variety) with the actual number, or how much, of analyzed and chosen variables (volume) there were in the final analysis. Williamson (2017) said the political economy is changing in higher education, and data science has migrated from the commercial sector into academics. This shift requires a basic knowledge of how data are defined. Torrecilla and Romo (2018) stated that one of the models necessary to understand the basics of any data tracking or analysis is the Gandomi and Haider the V construct.

Summary

The three V construct provides this study with an underpinning for deciphering the data outcomes as they relate to the perceptions and experiences of administrators in 4-year colleges of applying student data for tracking and predicting retention. This is done by incorporating the three V construct factors of volume, velocity, and variety into the semistructured interview questions. This construct will assist in data outcome interpretations in identifying participant experience or perception of data or student variable identification that relates to its volume, velocity, or variety. Heiner et al. (2007) stated that Attaran et al.'s model establishes an underpinning for the processes and tools needed in any data mining effort to operationalize decision making in order to synchronize data for planned improvement.

Literature Review Related to Key Concepts

The focus of this study will include the application of predictive approaches that can drive decision making in retention tracking initiatives in higher education and the efficacious identification of student data in this process. The first subsection of this review of current literature will provide a review of literature related to the tracking and predicting of retention in higher education. The ensuing section will review how student data are identified and used in retention. Next, I discuss literature on the importance of inclusion in student retention. The main themes that emerged include: defining retention in higher education, applying and identifying student attributes for institutional research, tracking and predicting retention in higher education, barriers to data mining.

Defining Retention in Higher Education

Retention in higher education and how certain populations are defined within the data mining process can be generalized or college specific (Dewberry & Jackson, 2018). What is noted as the current generalized definition of retention in higher education is the fall-to-fall comparisons as reported by the National Center for Education Statistics (2020). This national data clearing house, which also provides the Integrated Postsecondary Education Data System (IPEDS), is the agency considered as the expert in the national benchmarks for all higher education (Dewberry & Jackson, 2018; Sass et al., 2018; Swafford, 2017). Other terms that are associated with retention and have been used interchangeably are completion, persistence, and student success (Manyanga et al., 2017). Manyanga et al. (2017) continued and said that many institutions have defined and delineated these terms differently and a general agreement to the term retention is agreed upon in research. However, Manyanga et al. cautioned, generalizations about retention can be misleading due to the uniqueness of each institution, academically, culturally, and otherwise and should be considered carefully in research efforts.

Prior to the 1970s, student retention was seen as the reflection of individual attributes, skills, and motivation (Tinto, 2006). Tinto (2006) further stated that students who did not retain or persist were thought to be less able, less motivated, and less willing to foresee the fruits of this college labor. In short, students failed, not institutions. That view, and how institutions define student retention, shifted to consider the role of the environment, the institution, and level of connectedness a student internalizes for the decision to stay or leave (Olaya et al., 2020). This student retention definition continued evolving to what it is today and now has the student variable and data mining descriptors as part of this explanation (Garcia-Ros et al., 2019).

Nadasen and List (2017) stated that the difficulty is not of the definition of retention in higher education, it is the lack of information available to track or predict the retention of students, with a process for data mining and policy to inform best practices. This is evidenced by Elnozahy et al. (2019) who stated that for new students to retain, the supportive internal research needs to be accessible to inform practice on student variable identification for tracking of those existing and retained students fall to fall. This is discussed more specifically by Mahroeian et al. (2017), who defined and categorized the perceptions of its participants toward the use of analytics and data mining in New Zealand higher education. They found public and private 4-year upper management staff had knowledge of data in three main categories: structural, functional, and structural-functional. Mahroeian et al. further defined these categories via the participants' perceptions. Those who perceived analytics in terms of the structural aspects leaned toward quantitative elements such as statistics, digits, visualization, and metrics to inform decisions. Mahroeian et al., suggested further study to gauge the foundational perceptions and experiences in higher education related to data mining, use of analytics, and applying variables. Just as they sought to deliver a better understanding of current perceptions and values of analytics in higher education within the New Zealand by defining three functional aspects of data mining, I also seek to do the same regarding efficacious student variable application in tracking and predicting retention.

Applying and Identifying Student Attributes for Institutional Research

Understanding the student experience from academic, social, and functional aspects of institutional connectedness can only be recognized and measured if all student attributes are accounted for in internal research (Stage, 2000). Braxton (2019) suggested that student data could not be identified for research in retention until specific areas for future research were addressed. Braxton stated that these areas should be considered for data mining and defining student attributes: (a) continued study of sociodemographic characteristics of students, (b) the role of organizational behavior, (c) student environments nested within different institutional settings, and (d) the effects of student sub climates (p. 132). However, one such attribute being considered from a psychology and emotional health point of view, student external commitments, is traditionally not thought of as a measurement assigned in tracking retention in higher education (Tight, 2020). Tight (2020) continued and stated that institutions continuing to focus on the obvious attributes such as race, socioeconomic status, SAT, and gender, are doing a disservice to themselves and students by not attributing external commitment attributes to retention research tracking.

A trending practice in higher education has been program review (Conrad & Wilson, 2020). Conrad and Wilson (2020) suggested that institutions consider program review as an opportunity to assess student retention at program and course levels. In doing so, Conrad and Wilson continued, student attributes may emerge that can be used as variables for tracking retention initiatives both at granular and institutional levels. Manyanga et al. (2019) stated that few institutions truly have a retention agenda nor agreed upon student attributes to apply as variables in these retention efforts. In various retention models that have been discussed over the past few decades, Manyanga et al. found that assessment and review at the course and program levels every 3 years should be best practice. They continued and said that this best practice serves not only to inform internal stakeholders of student satisfaction but to also reveal certain student attributes of those who retain and can be applied as variables for tracking and predicting retention. Premalatha (2019) agreed and stated, in her review of traditional outcome-based education that included program review outcomes, that this model does not include a process for identifying student attributes for retention. Premalatha continued that new processes should be considered for outcome based education and program reviews to include an intentional look at student attributes within these internal audits for student success measurement and tracking for retention.

Higher education institutions have been faced with numerous problems ranging from reduced student population, poor student performance, reduced funding and lack of transparency in its operations (Baer & Norris, 2016). Krieb (2018) addressed this issue from the poor student performance perspective. Krieb found that more study is needed to identify additional student data for tracking retention to inform practice and policy overall in higher education. Krieb brought a new awareness of the importance in identifying student data for tracking retention at his institution, which is an outcome I hoped for this research as well.

Tracking and Predicting Retention in Higher Education

Users of big data for retention tracking have shown inconsistency in its application in higher education (Daniel, 2015). Daniel (2015) stated that this inconsistency affects decisions made with respect to the experiences of the users, institutional policies, and processes adopted by the institution. Daniel’s focus on big data management in higher education emphasized identifying student data for tracking initiatives as part of the big data management process for retention. Sperry (2015) stated that there are valuable attributes to be considered in precollege student data when drafting processes for retention initiatives. The importance of efficacious application practices for student data in tracking and predicting student retention is evidenced by Niebel et al. (2019) who said that some of the benefits of such practices are increased retention, financial returns, and satisfaction of customers.

Tracking retention in higher education should consider the student body in its entirety but not necessarily the identifying the same attributes applied as tracking and predictive variables (Saunders et al., 2016). Saunders et al. (2016) indicated that subsets of psychometric tools should be considered for retention tracking and potentially predicting the retained student. They stated that this is not only complimentary to the academic and demographic data that is commonly used in retention initiatives but also to ascertain a students' self-efficacy, confidence, and engagement for both in the classroom and campus activities for connectedness. Xerri et al. (2018) agreed and stated that the influence of student connectedness showed a direct relationship to the motivation to study and therefore an increase in academic success that ultimately results in retention and completion. Xerri et al. suggested that factors influencing this connectedness are largely unknown and subsets of student psychosocial attributes would assist in not only gaining this knowledge but further understanding the student journey in higher education. This process for gathering subsets of psychometric or psychosocial data for tracking and predicting retention was also suggested by Ganotice and King (2014). They stated that the connectedness of students can potentially be measured from the perceived support of faculty, parents, and peers—the most salient of these being that of the support of their peers.

A current trend in higher education for student retention initiatives are high impact practices (HIP; Provencher & Kassel, 2019). HIP are intended to bolster the support and success of second year college students (Provencher & Kessel, 2019). They continued and stated that early data has shown improved retention with students who are involved with HIP. However, Provencher and Kessel (2019) were concerned that bias has occurred with student selection for HIP and research should focus on institutions that shown intentional equity of the HIP process, so retention data are not skewed. Murray (2015) stated that HIP have shown increased student retention when considering student library use and involvement. Murray suggested that student attributes for library use and frequency be mined and used as retention tracking and predicting measures. In a similar study, but a focus on asynchronous discussions boards for HIP, Perrotta (2020) stated that this HIP also showed influence on increased student retention in the history program being studied. Perrotta said that findings from this study set the stage for an increased pursuit of student attributes from HIP and suggested that further research from qualitative study would benefit.

Barriers to Data Mining

Lomet (2017) noted the importance of the protection of student data, the buy in of faculty, and the cost effectiveness of any data mining tool for higher education. Bughlin (2016) agreed and added that gathering big data for identifying variables requires a system to mine and target an institution specific initiative but the barriers will be far greater before the benefits can be realized. Nadasen and List (2017) stated that the problem is the lack of information available to track or predict the retention of students with a process for data mining and policy to inform best practices. Soares et al. (2016) noted the lack of literature and research available to guide practice because much of the literature is on Learning Management Systems (LMS), a specific academic group, or small cohorts for identifying retention variables that only provides a narrow scope of understanding in data mining. Wilderotter (2020) agreed and stated that a predictive analytics model is needed for higher education that can be customized to specific institutional needs while still underpinning best practice.

Important components to best practices in retention initiatives in higher education are the attitudes and perceptions of administrators who have the responsibility for apt use, defining, and application of, student data (Alsharari & Alshurideh, 2020). Staff and faculty concerns of protected student information is another barrier to college administrators' application of data mining protocol for predictive analytics (Ekowo & Palmer, 2016). Albalowi and Alhamed (2017) also addressed this concern, providing a number of problems that have affected the adoption of data mining for student data identification in higher education such as the culture or environment, absence of appropriate infrastructure, and ethical issues related to the students.

Culture or Environment

Chaurasia et al. (2018) believed that user perceptions of analytics and data mining tends to contribute to its acceptance and use as a medium for generating variables for institutional research. They further added that many institutions do not have a culture of data-based decision making because of these perceptions and therefore identification of student data to assess learning as well as overall retention are problematic (Chaurasia et al., 2018). Gagliardi et al. (2108) stated that the most significant challenges to the adoption of data mining, specifically for variable identification used for internal research in higher education, has been limited to perception of data managers toward the institutions' culture of this work. They continued by saying that data manager inability to comprehend the benefits associated with the use of campus-wide analytics can adversely affect an institution's capacity to compete, perform their operation, develop a learning culture, and retain students by potentially not wanting to share data, based on this perceived data culture (Gagliardi et al., 2018). Cope and Kalantzis (2016) agreed and stated that those higher education administrators who value introducing new methods of thinking as well as a means of data-informed practice are typically met with barriers. They went on to say that these barriers are the increasing cost associated with the gathering, storage, analysis, and application of this data that is siloed and decentralized. In addition to culture, Hadwater et al. (2018) stated that the barriers that have contributed to the slow adoption of data mining efforts that identify student data for institutional research include existing infrastructure, and institutional policies.

There is growing pressure for higher education to be a culture of evidence (Hora et al., 2017). Hora et al. (2017) stated that data mining techniques applied to higher education gives an institution the capabilities to improve institutional level operations such as targeted recruitment for efficient admission operations for undergrad, international, and graduate programming. Andrews and Lemons (2015) cautioned that institutional level culture is not enough. They stated that for a decision-making culture based on data evidence to occur, this practice needs to permeate to staff and faculty who are responsible for the day-to-day services with students. Faculty still make decisions based on personal experiences rather than data (Andres & Lemons, 2017). In any higher education institution, there are multi levels of practice that feed into the culture of learning (Klimek & Klimek, 2020). A seemingly monumental barrier to a productive shift to a data driven culture will be the shared reality, vision, and trust of the IT department, administrations, and faculty, said Klimek and Klimek (2020). They stated that for dynamic development and dissemination of data technologies to occur, small steps with data driven problem solving that require internal stakeholder integration can begin the road to barrier removal.

Infrastructure

Cope and Kalantzis (2016) said that systems used by institutions of higher learning do not support interoperable data analysis, suggesting that a wide range of data for high level use and classroom data are stored in multiple online repositories and this creates problems for narrowing down variables to identify as targets for internal research efforts. Matsebula and Mnkandla (2017) noted that the absence of an appropriate infrastructure specifically tailored for mining student attributes and behavior characteristics in identifying variables has contributed to the inability for analytics to support decision making in many facets of student success in higher education. Avella et al. (2016) stated that student attributes can be collected, managed, and used to identify variables for retention in many of the LMS purchased by institutions. However, Avella et al. continued by saying that data mining from these LMS can be difficult. Albalowi and Alhamed (2017) agreed but pointed out that although faculty pushback is the biggest barrier, the benefits of the data mining capabilities in LMS can include improved student placement, better enrollment rates, and enhanced attendance and academic warning systems. Some institutions of higher learning have utilized certain LMS to evaluate the quality of education offered, determine the enrollment rate, share profiles, acknowledge the supported required in improving the learning experience, among other benefits

(Avella et al., 2016). Avella et al. continued by stating that these efforts are frequently siloed and many still use manual data entry reporting such as excel sheet storage and updates. Manual tracking systems and siloed data practices have proven to be ineffective in resolving student retention in higher learning institutions (Matsebula & Mnkandla, 2017). Williamson (2017) acknowledged this and stated that educational data science has predictive algorithms for retention in its grasp, but the level of expertise, manual tracking, and available workforce can be a barrier. Williamson added that retention data should be housed as a centralized data warehouse, but the responsibility of its use and application should be widely dispersed with proper training and respect for protected student information, as ethical issues are an ongoing concern.

Institutions of higher learning face new challenges relating to student information uptake and internal analysis (Arendsdorf & Naylor-Tincknell, 2016), including information related to global economics, political change, and ensuring the programs they offer are relevant to market needs locally and nationally. Chaurasia and Rosin (2017) added that, due to competition, institutions find themselves under immense pressure to analyze and decipher large data sets, as doing so puts them ahead of the competition. However, Stefanova and Kabakchieva (2017) contended that literature is inadequate to support the knowledge base needed to apply data for retention efforts. Shein (2020) agreed, stating that the knowledge base needed for data managers in higher education is simply not in the literature.

Utilization of student data applied as performance indicators in tracking retention in higher learning has been considered effective (Varouchas et al., 2018). Varouchas et al. (2018) continued by stating that in higher education, data mining for student variable identification for internal initiatives can be obtained from several sources such as social media, information and learning systems used in the institution, and swipe card data. Data mining processes such as these include a high velocity, volume, and variety of raw data that is needed to be applied in tracking or predicting retention (Attaran et al., 2018). The problem with this data mining is the lack of consistency, knowledge of data application best practices, and sensical policy to align such endeavors (Varouchas et al., 2018). A data mining model in educational settings is best used concurrently with data analytics and the knowledge base required to understand the diversity, size, and speed of data (Huselid & Minbaeva, 2019). The updates to the higher education data mining systems, however, are long overdue (Tsai et al., 2015) and the research is not available for higher education administrators to use as guides for retention tracking process and practice. Tsai et al. (2015) continued by saying that management, processing, and application of variables from large sets of data to track and predict success cannot be accomplished by simple excel sheet formulas that were once considered traditional means. The collection, management, and identification of variables for retention requires a more sophisticated approach.

Ethical Issues

Roberts et al. (2016) indicated that the use of analytics tools in the higher education sector has outpaced the ethical aspects associated with its usage. From the perspective of higher education, data analysis related to students has comprised of demographic details, enrollment survey results, student course assessment, the use of library facilities, the academic performance of students, among others (de Freitas et al., 2015). Elhassan and Klett (2018) suggested that an ethical perspective is needed to consider student’s participation in decision making in order to promote a healthy institutional climate so unbiased student data is being gathered from student attributes and behavior characteristics needed for identification of variables for retention by the administrators.

Ethical concerns related to data mining for student data is captured in the Roberts et al. (2016) study. They indicated that the use of analytics tools in the higher education sector has outpaced the ethical aspects associated with its usage. Roberts et al. continued that the nonexistence of the students’ voices regarding the use of data mining has presented challenges related to the acceptability of student attributes and behavior characteristics use for identifying variables for further study. From the perspective of higher education, data analysis related to students has comprised of demographic details, enrollment survey results, student course assessment, the use of library facilities, the academic performance of students, among others (de Freitas et al., 2015). Elhassan and Klett (2018) suggested that an ethical perspective is needed to consider student participation in decision making in order to promote a healthy institutional climate so unbiased student data are being gathered from student attributes and behavior characteristics needed for identification of variables for retention by the administrators. Further, Lacerenza et al. (2018) stated that successful teams produce desired outcomes but it is critical that team members demonstrate effective processes to achieve these outcomes. They continued and stated that team development interventions are salient to team survival but adherence to data policy and ethics is salient to institutional survival.

Summary and Conclusions

Major themes in the literature were discussed in relation to the key concepts of defining retention in higher education, applying and identifying student attributes for institutional research, tracking and predicting retention in higher education, barriers to data mining. Defining retention in higher education can be both generalized and institution specific (Dewberry & Jackson, 2018) depending upon the college mission and accrediting body expectations (Conrad & Wilson, 1985). Tight (2020) stated that higher education is missing an opportunity in tracking retention by not considering attributes to apply as variables directly related to student external commitments.

What is Known

What is known about tracking and predicting retention in higher education is that there is an overabundance of large unstructured data that needs to be disaggregated to find the nuggets of significance for internal research (Huselid & Minbaeva, 2019; Shein, 2020) and the old system of manually gathering data from siloed data systems that do not integrate, further increases institutional instability (Soares et al., 2016). Research literature yields plenty of data mining options for higher education in regard to LMS (Krieb, 2018) but these studies focus on variables that only serve academic purposes and not those that inform policy and practice on campus wide data mining integration, experiences and knowledge base of data administrators, nor the process for identifying student data in tracking or predicting retention (Avella et al., 2016; Baer & Norris, 2016).

What is known about identifying student data from attributes and behavior characteristics that are needed for tracking and predicting retention can be obtained from a number of sources such as social media, information, and learning systems used in the institution, and swipe card data among others (Varouchas et al., 2018). However, the problem with this data mining is the lack of consistency, knowledge of data application best practices, and sensical policy to align these undertakings (Chaurasia et al., 2018). This all plays into the ethical dilemma that poses barriers in higher education if aligned policies for best practices are not transparent to the staff, faculty, and students regarding the use, storage, and outcomes of protected data (Elhassan & Klett, 2018).

What is not Known

What is not known in the areas of student variable identification and its place in the efficacious tracking and predicting of retention in higher education are the perceptions and experiences of the data administrators to this process that would directly inform policy and practice (Gagliardi et al., 2018; Hadwater et al., 2019). Further, data managers inability to comprehend the benefits associated with the use of campus wide analytics can adversely affect the institutions' capacity to develop a learning culture and retain students by potentially not wanting to share data, based on a perceived data culture that may exist or not (Hadwater et al., 2019). Higher education leaders need to know that the actual barriers that may exist given the data manager knowledge base and a culture of data support or not have contributed to the slow adoption of data mining efforts that identify student data for institutional research (Ekowo & Palmer, 2016). These perceptions and experiences from data administrators in higher education can prove to be valuable in the evolution of data analytics for institutional stability (Albalowi & Alhamed, 2017).

Gap in the Literature

This study seeks to fill the gap in literature that is needed to inform the practice of identifying student data for tracking and predicting retention. Further, the outcomes of this study aim to fill the gap in the literature regarding what is not known regarding the process of data mining for student data, and that is the experiences and perceptions of the college administrators responsible for these efforts. I also seek to have similar results as Krieb (2018) in bringing awareness and understanding to those administrators in higher education needing research results to inform a gap in the practice for identifying student data in tracking and predicting retention. By accomplishing these objectives, this current study will fill this informational research gap, thus benefiting future researchers who may desire to explore and add on this topic.

Transition

The next chapter will detail the research design and method as well the process for participant selection. Further, in Chapter 3, a discussion of the internal and external validity will be explored, the role of the researcher, and data analysis plan and treatment of the research data. A final summary will unify the information and complete the chapter.

Chapter 3: Research Method

The purpose of this basic qualitative study is to explore and describe perceptions and experiences of administrators of 4-year colleges and their identification and application of student data for tracking and predicting retention. In this chapter, the role of the researcher as well as methods, design, and validity of research is discussed in relation to the purpose of this study. A detailed description of participant recruitment and selection strategies is discussed as well as the data analysis plan. The data analysis plan includes a discussion of internal and external validity as well as adherence to ethical procedures. Chapter 3 ends with a summary and segue into Chapter 4.

Research Design and Rationale

I used a bbasic qualitative research design to address the research question: What are the perceptions and experiences of higher education administrators in terms of the application of student data targeted for tracking and predicting retention? The central phenomenon of the study is the application of student data for tracking and predicting retention and how this process is perceived or experienced by administrators responsible for such responsibilities at 4-year institutions. I wanted to make sense of the data analysis process and inform practice in higher education regarding how student data may be identified and influence retention initiatives. According to Barbour (2014), researchers should confer with participants by asking questions and inferring meaning from responses.

The basic qualitative research design is appropriate for this study because the RQ is broad and open to unexpected findings. Knapp (2017) said the basic qualitative study is appropriate to explore experiences of participants with knowledge of the topic and ascribe meaning to those experiences. The basic qualitative design is also appropriate to explore college administrators' perceptions about the phenomenon of efficacious application of student data for tracking and predicting retention. This design allows participants to provide thick and rich accounts of their experiences and perceptions (Korstjen & Moser, 2017; Merriam 2015). Also, basic qualitative research is used to examine natural circumstances in which individuals function to provide a practical understanding of real-world problems (Korstjen & Moser, 2018).

Role of the Researcher

With the basic qualitative research design, the role of the researcher is to be the instrument for gathering and analyzing data (Silverman, 2016). Qualitative researchers influence the research process because study participants interact with researchers. In this study, the interview process allowed relationships to be built. This influences the research process and its findings, which is why it is important for me to be transparent about my perspectives as the researcher and explicitly acknowledge any subjectivity.

My professional role is director of retention and completion at a 4-year private nonprofit university. Inherent biases can threaten the trustworthiness of the study if not kept in check. Shufutinsky (2020) suggested self-checking, which includes reflection, feedback, and mindful consideration during qualitative research. Shufutinsky said qualitative research is generally rooted in interpretivism, and therefore, the researcher is responsible for the interpretation of participant responses. I used bracketing and epoche methods to mitigate preconceptions and presuppositions that could taint the research.

Epoche practices are those practices that allow for active suspension of assumed understandings by journaling throughout the research process and note taking during data collection (Shufitinsky, 2010). Bracketing and epoche are often used interchangeably in practice (Butler, 2016). The researcher, as the main instrument of the research, must be constantly conscious of internal ideas, perceptions, values, prejudgments, and connections to the topic under study (Creswell, 2013). Journaling throughout the study process in its entirety and reflective note taking during data collection helps mitigate research bias through awareness of self and processes.

As a qualitative researcher, I employed empathy as well as distance. Empathy entailed putting myself into participants' situations in order to better understand their intent and meaning. Distance involves necessary awareness of my own values, which can negatively influence data collection, and as the researcher, I must remain nonjudgmental and nondirective. I did not have any known relationships with participants as coworker or supervisor. This removes any potential power relationship with participants. No information was purposefully omitted or altered. I acknowledged the importance of being aware regarding my role during processes of collecting, analyzing, and interpreting data, as well as mitigating preconceived biases by conducting a test run of interviews. These efforts mitigate bias.

Methodology

This section includes procedures for coding and analyzing data, as well as methods to ensure trustworthiness and ethics in research.

Participant Selection

The participant sample consisted of approximately 10 administrators from 4-year U.S. colleges. Sample size result in qualitative research is determined by data saturation (Etikan, 2016; Guetterman, 2015). Sample size for qualitative studies can vary when using interviews for data collection. To recognize that data are saturated, some analysis must occur during data collection. The researcher must notice when participant responses become repetitive. I estimated that no more than 12 participants were needed to reach data saturation; this was determined during the interview process. According to Patton (2015), it is an acceptable practice in qualitative research to check with interviewees for more information to enrich or clarify data to meet data saturation. If saturation is reached, there is no need to seek additional interviews because themes, patterns, and concepts repeat, with no new information being collected (Merriam & Tisdell, 2016). Selecting an appropriate number of participants for a study leads to manageability of the data results, richness of data, and relevant participant characteristics.

Chosen participants had decision-making responsibilities in their institutions. Participants for the study were chosen via criterion-based selection, a form of homogenous purposive sampling. Participants needed to have student data identification or tracking and predicting of retention initiatives among their responsibilities. They were identified through institutional public websites that list higher education administrator profiles and contact information. The first 10 individuals identified as fitting roles and criteria for participation in this study were selected and sent recruitment letters via email. Email addresses were retrieved from public websites that were randomly chosen.

What follows are procedures for how participants were identified, contacted, and recruited. An IRB approved letter of consent was sent via email. This consent outlined the intent of the study, participants identity protection, treatment of data, and statement of voluntary participation. Those who agreed completely filled out and signed the consent form and returned it to my personal Gmail address listed in the consent form. Depending upon participant location, the interview choices consisted of face to face, virtual, or phone. Given the 30-day time frame that was presented in the introductory request letter, the participants specified the best days and times for the interview and the preferred format. The format of semistructured interviews are flexible and versatile, making them a popular choice for collecting qualitative data (Kallio et al., 2016). They are a conversation in which the researcher knows what she/he wants to cover and has a set of questions and a foundation of knowledge to help guide the exchange and can be done face to face, phone or virtual, depending upon research and participant preference (Magaldi & Berler, 2018). Given the current COVID-19 restrictions the goal was to create a safe space so the participant felt comfortable to reflect upon his or her own personal experiences while maintaining social distancing protocol (CDC, 2020).

Instrumentation

Data collection was achieved through researcher-produced questions for semistructured interviews. The questions found in the Appendix A, are based on the literature review conducted relating to data mining practices for student variable applications in tracking and predicting retention in higher education, as well as the conceptual framework models chosen for this study. Also, in designing queries for interviews, I was sure to use language that most participants are likely to understand (Rubin & Rubin, 2012). Literature and the conceptual framework for this study guides the development of the research question, but it was important to develop and use open ended interviewing methods to avoid guiding participants' answers (Rubin & Rubin, 2012). I started with what Rubin and Rubin (2012) call a tour question that has participants talk about their broad activities in their administrator role before asking about specific experiences in student data applications in retention initiatives. The tour question is intended to open a frame of context for participants to consider in a broad sense, while the accompanying probes are worded to promote confirmation, clarification, sequence, continuation, elaboration, and credibility (Magaldi & Berler, 2018). In this case, the questions for phone, virtual, or face to face interviews are appropriate for qualitative research given its fluidity and participants' ability to elaborate on their answers (Brinkmann, 2016). Each interview will last for approximately 60 minutes to provide each participant with enough time to express and elaborate on each question (Magaldi & Berler, 2018).

Basis for Instrument Development

The semistructured interview questions were created by me and follow protocol from previous qualitative studies (Castillo-Montoya, 2016; Kallio et al., 2016; Magaldi & Berler, 2018). Kallio et al. (2016) used a protocol for semistructured qualitative interviews that included five phases: (a) identifying the prerequisites for using semistructured interviews, (b) retrieving and using previous knowledge, (c) formulating the preliminary semistructured interview guide, (d) testing the guide, and (e) presenting the complete semistructured interview guide. I referred to these steps during the drafting of the semistructured interview questions.

In a similar manner of study, Castillo-Montoya (2016) developed the interview protocol refinement (IPR) framework for the development of an interview protocol. The IPR method aims to support efforts in reinforcing the reliability of interview protocols in qualitative research. The framework includes, constructing the interview questions and ensuring interview questions align with research questions, has been completed (see Appendix A). In this study, the interview protocol was used to address the RQ. To guide my creation and alignment of the interview protocol, I used the Types of Interview Questions from the IPR framework (Table 2). I also used the Types of Interview Questions table as a reference to ensure internal validity (Castillo-Montoya, 2016). Referencing this process ensured clarity, focus, and sufficiency of the questions to prompt accurate responses that are aligned to the RQ.

Table 2

Types of Interview Questions

Types	Explanation of Type
Introductory	Questions that are relatively neutral eliciting general and nonintrusive information and that are not threatening
Transition	Questions that that link the introductory questions to the key questions to be asked
Key	Questions that are most related to the research questions and purpose of the study
Closing	Questions that are easy to answer and provide opportunity for closure

Note. From “Preparing for Interview Research: The Interview Protocol Refinement Framework” by M. Castillo-Montoya, 2016, *The Qualitative Report*, 21, p. 823.

Magaldi and Berler (2018) said interviews are an accessible, affordable, and effective method to understand a phenomenon in the world of research. Their approach suggests that semistructured queries are an interpretive framework where the data collected is not viewed as evidence of the truth or reality of an experience but rather a context-bound and subjective insight from the participants. In this way, Magaldi and Berler suggested that the researcher needs to be open to new insights and to honor the participant’s experience in data collection by using the basic qualitative design to abut this method that is exploratory in nature and permits the collection of rich data which can answer questions about which little is already known.

Procedures for Recruitment, Participation, and Data Collection

Once IRB approval is received for this study, a criteria-based sample was recruited to yield approximately than 12 administrators from a 4-year, U.S. institution. Potential participants were identified through a higher education random google search of 4-year institutions' public websites. Email correspondence to those academic leadership having contact information listed on their institutions' public site will commence to those who have a job title, job responsibilities, or job description that involve data mining, student variable identification and application in research initiatives, and participation in tracking and predicting retention on any level at their institution. This initial email will contain the details of the study on the 30-day timelines for the interviews, volunteer consent, treatment of the data, confidentiality of the participants, and the purpose of this study.

A minimum of 50 email invitations were sent for the first round of recruitment to seek the approximately 12 participants. Return emails of interest from potential participants will yield a self-identification for meeting the approved criteria. This will continue until approximately 12 participants are identified. Each week an additional 25 institutions were googled for participants meeting criterial and contact information displayed on their institution's public site. This continued each week until the minimum number of 10 but no more than 12 participants meeting the criteria and accepting the terms is met. Participants who returned the emails with interest received the letter of informed consent within 24 hours to review and sign. Any participant that showed interest but did not respond were sent two additional follow up emails to confirm their interest or not. Should there have been participants who were unwilling for any reason to continue in the study at any time were told they may contact me via my listed email and I would have removed them from the study.

All interviews were recorded with the Google transcribing tool that is a voice to text software. The use of this software supports the need to ensure valid and reliable data from the interviews as well as have a cross checking system for me to review for accuracy (Creswell & Poth, 2016; Given, 2008). This process was performed while keeping the participants' identity protected and honor the confidentiality of the participants, in case they would inadvertently provide identifying information and need to be redacted. The interviewees were informed of potential follow up, within 2 weeks after the interview, via email if further clarification is needed. At that time, all participants will receive an email stating that the interviews are completed, and the analysis has begun. Any participant interested in viewing the final study can email a response and a copy was emailed upon completion.

Data Analysis Plan

What follows are the data analysis approaches for this study. I used Feng and Behar-Horstein's five-step procedure to analyze the data collected for the study:

1. Step one is data cleaning and participant coding alignment to responses in an excel sheet format or manual first round transcript coding.
2. Excel sheet data or direct transcript was imported to NVivo software system.
3. Word frequency analysis will then be conducted through NVivo word frequency query feature.

4. Text coding and reference extracting includes the text search query feature to identify the most frequently occurring words to code the responses content of all sentences or paragraphs for each participant within each question. NVivo refers to these words as nodes. Nodes are also known as categories in the qualitative induction coding process. Content that includes the most frequently occurring words were identified as references of the nodes. The text coding summary from NVivo shows the number of references for each node or category.
5. Matrix coding, mind mapping, and data relationship queries for continued inductive analysis allow comparisons across and between different nodes or categories and references to categories within the participant responses for themed focus.

Software programs can be useful in organizing large amounts of data and assist the researcher with assigning codes to data (Korstjen & Moser, 2018). The use of software can simplify the analysis process without sacrificing any significant meaning found within the data. I used inductive coding to tag meanings in the perceptions and experiences of student variable identification from participants (Merriam & Tisdell, 2015). Given the probability of diverse responses, inductive coding was used as a cross check to NVivo in the matrix coding and inductive analysis step of Feng and Behar-Horstein's data analysis approach. This will continue with each component of the RQ: perceptions and experiences of student variable application to research, perceptions and experiences of student variable identification in tracking and predicting retention, and perceptions and experiences of student variable applications in tracking and predicting retention. The bigger categories are the overarching themes while the subcategories are theme supporters (Korstjen & Moser, 2017). NVivo software analysis uses the word nodes for the subcategories and theme supporters as references to nodes that feed into the major themes to be addressed in the RQ (Feng & Behar-Horstein, 2018; Welsh, 2002). This is where the participants' responses become a story from the data. The themes can tell the same story from different perspectives, or several different stories that connect with each other (Given, 2008). This final phase in analysis involves connecting the stories through connecting themes in data with word clouds, frequencies, percentages, or tables to finalize the analysis from NVivo and researcher notes (Babchuk, 2017).

Once the data are collected, I analyzed it through the matrix coding approach. I also employed an iterative process throughout the data analysis process for the purposes of organizing and managing the data (Babchuk, 2017; Given, 2008; Merriam, 2015). This process will involve labeling interview notes, transcripts, and participants with confidential identifiers. This process included organizing key elements of the data relevant to this study, including a priori and axial coding systems (Babchuk, 2017; Merriam, 2015). The a priori codes were created from the conceptual framework supporting this study from Attarran et al. (2018), and Gandomi and Hader (2015). A priori codes were highlighted in the transcripts as key words and phrases. During the open coding procedure of the study, I used repetitive words and phrases of meaning that emerge from the data, as well as those seen as emphasized by the participants, (Korstjen & Moser, 2017) to be designated as codes (Merriam & Tisdell, 2015). During the final, axial coding I categorized codes into groups and identify patterns that will become major themes (Lichtman, 2017). This final process formed the basis for my findings and conclusions of this study (Creswell & Poth, 2016).

In basic qualitative studies a researcher must identify and assess discrepant data (Levitt et al., 2017). Discrepant data is an occurrence that cannot be accounted for or explained and can signal defects in the data (Korstjen & Moser, 2018). It was important to examine and confirm discrepant data, the inconsistent pattern of data, with that of the other resources and review with participants. Maxwell (2008) stated that distinction between categories or themes may be the source of negative or discrepant data and can be resolved with probing questions or follow up review with participants. Once this is completed, the discrepant data will be shared in the analysis and findings of this study and explained (Creswell & Poth. 2016).

Trustworthiness

Trustworthiness in qualitative research must demonstrated to show proper methods and rigor were used throughout the data collection and analysis process (Babchuk, 2017). Protocols in trustworthiness include demonstrating credibility, transferability, dependability, and confirmability (Amankwaa, 2016; Korstjens & Moser, 2018). Maxwell (2008) stated that researcher bias is a thread throughout the research process that provides a quality of awareness and that we should not suppress our primary experiences. He continued and stated that, conversely, we do not allow this awareness and related experiences to overwhelm nor drive the research process, but rather elevate mindfulness and use it as part of the inquiry process. Lichtman (2017) stated that the researcher is the conduit through which participant relationships are built to yield insight in the data. Lichtman explained that self- reflection and subjectivity within the steps of building participant comfortability in the interview process for data collection does not cause a paradox or confusion. Rather, the researcher creates the awareness needed to show the sense of self and therefore demonstrates deep understanding that directly influences all aspects of trustworthiness in qualitative research (Lichtman, 2017).

Credibility

Credibility was authenticated in this study by assuring the participant response was received as it was intended through member checking (Patton, 2014). As stated by Korstjen and Moser (2018), I repeated probing questions, take side notes during the interview, and sharing the tentative results of data analysis with the participants via email. An agreement with Madill and Sullivan (2018) I used member checking to repeat the interview questions with different tone or wording without changing the meaning. I provided participants with the opportunity to restate their answers during the interview and amend the meaning of their statements after the interview (Madill & Sullivan, 2018; Patton, 2014). I did, during interviews, noted vague responses, repeated questions with clarifications, and reflected participants statements back to them for clarification (Madill & Sullivan, 2018).

Another credibility authentication method that I used is reflexivity. Korstjen and Moser (2018) described this as the process of critical self-reflection about oneself as the researcher and one’s biases, preferences, and presumptions as well as the relationship to the participants and how this relationship may affect their answers to questions. As

Maxwell (2008) advised, I maintained a reflexive, internal credibility process during the semistructured interviews. By journaling and taking notes throughout each interview, I monitored my own explicit and implicit assumptions in all phases of this qualitative study to enhance credibility (Maxwell, 2008).

A third process to confirm credibility in the study is how discrepant data was handled. Negative or discrepant data is described by Patton (2014) as exceptions to the patterns found in the data. When negative or discrepant data occurs, I reviewed and reflected from a cross checking perspective via interview recordings, researcher memos, and journal to determine useful support of the study as suggested by Bashir et al. (2008). This allowed me to record the experiences of participants within and beyond the immediate context (Korstjen & Moser, 2018). So, I continually checked and verified the data processes to ensure that the results are robust, rather than a simple justification of any assumed findings (Spiers et al., 2018).

Transferability

Transferability relates to the ability to transfer the results of the study to a population differing from the one used in the data collection (Amankwaa, 2016; Babchuk, 2017; Kallio et al., 2016). Participants were selected from those serving in decision-making positions in higher education from 4-year, U.S. institutions. Criteria-based selection was used to recruit higher education administrators with specific knowledge in data mining, student variable identification and application for internal research, and the tracking and predicting of retention on any level at their institution. By providing this rich description of the participants and the research process, the reader of this study can decide whether the findings are transferrable to their setting (Korstjen & Moser, 2018). Korstjen and Moser continued and stated that the reader, not the researcher, can make the transferability judgment. The job of the researcher is providing as much context as possible so lens can be clear for the reader to see applicability to their setting or not (Arensdorf & Naylor-Tincknell, 2016).

Dependability

Dependability is also necessary in a basic qualitative study to show reliability of the data collection and the analysis (Amankwaa, 2016; Babchuk, 2017; Kallio et al., 2016). For this study, audit trails will be easily accessible in a few forms from the start of this research study to the development and reporting of the findings as needed to show transparency as stated by Korstjen and Moser (2018). Once such audit trail can be found in the records of the research path that are to be kept throughout the study and 5 years after its completion. I have this information password protected and kept at my home office with desk drawer key that I alone can access. Another audit trail used in this study was the a priori coding system protocol used by the researcher for the interview questions and audio transcription for cross checking interview data of the participants as suggested by Babchuk (2017). Finally, the handwritten reflexivity notes and journal will be accessible as well as the recordings of the participant interviews for review as needed (Silverman, 2016). This protocol follows a specific stage by stage process from general memo taking and journaling through reflexivity, taking the priori coding in the interview questions that can be further used during the data collection process through deductive coding and cross checking with the NVivo software (Feng & Behar-Horenstein, 2019).

Confirmability

Confirmability refers to objectivity or the ability of others to confirm findings (Stahl & King, 2020). Confirmability refers to the researcher's transparency and documentation of processes (Korstjen & Moser, 2018; Nowell et al., 2017). As Koch (1994) recommended, I included markers, such as the reasons for analysis choices, so that others can understand how and why analysis decisions were made. I enhanced confirmability in this study by describing the process used for data collection and analysis as suggested by Meadows (2003). I provide a detailed description of the sequence for data collection, coding, and analysis to deliver a clear and well-defined accountability for the process (Bochner, 2018; Meadows, 2003).

Ethical Procedures

I submitted a request for internal review board (IRB) approval before conducting any research with human participants. This process is in place to hold accountability for researchers. The IRB document contains questions that must be answered by the researcher in regards to participant selection criteria, informed consent document, contact intended for any vulnerable populations, instrumentation tool and how it was used, and treatment of data. Once all research protocol met the standards for the protection of participants, then approval was given (IRB Approval # 04-22-21-0672595). Upon IRB approval the potential participants were contacted via email with informed consent that includes the purpose of the study, type of data collection, and any risks if indicated. Further, the informed consent clearly stated the voluntary nature of participation and ability to withdraw at any time as well as complete confidentiality during and concluding the process of the study. The study did not require the use of vulnerable populations. Further, the participants of this study could leave at any time during the process. The semistructured interview questions approved by the IRB are found in Appendix A. I did not be conduct this research in my direct work environment nor with any higher education professional known to me, so these rule out any potential conflict of interest or power differentials. I have chosen not use participant incentives for this study.

Treatment of Data

All email correspondence taken place beginning with participant recruitment up until data analysis will remain in a password protected hard drive. All transcribed audio recorded data are kept within google docs account that only I can access and is password protected. Any handwritten notes to support data in hard copy file format are housed in my home office within a locked drawer and I am the sole key holder. Participant names were coded to protect anonymity during data analysis and when delivering the study findings. Confidentiality was maintained throughout the process by changing the names of the participants and general references to 4-year schools without identifying name of schools. It is required to keep all data and results for 5 years after the completion of the study (Babchuk, 2017; Knapp, 2017). After the 5-year period is concluded all files will be either shredded or deleted as indicated for hard copy and electronic copies of the research study.

Summary

This chapter explored all that is involved in participant selection, recruitment, and the data collection and analysis that comes from the instrumentation. Trustworthiness and ethical procedures being followed for this study were also briefly discussed. Once completed, this study will offer an account of the perceptions and experiences of administrators of 4-year, U.S. colleges regarding the application and identification of student data for tracking and predicting retention. Participants are selected based on certain criteria needed in either their job title, job responsibilities, or job description. Recruitment for at least 10 but no more than 12 participants began with a random Google search of all 4-year, U.S. colleges that have public websites. Within these websites, another search was conducted to view any administrators that may meet the criteria for data mining, student variable identification and application to internal research efforts, and predicting and tracking retention on any level at their institution. Contact information posted allows for email and phone contact to recruit participants. Protocol was followed for the IRB approved informed consent and the researcher produced semistructured interview questions. The 30-day timeline started the day the participant sent back the approved and signed informed consent form. This 30-day timeline allowed for flexible dates and times for participants as well as any time needed for brief follow up. In the next chapter, I reflected upon the details of the study results through the discussion of the data collection, analysis, and trustworthiness of this study.

Chapter 4: Results

The purpose of this basic qualitative study was to explore perceptions and experiences of administrators of 4-year colleges in terms of their application of student data for tracking and predicting retention. This study was driven by the RQ: What are the perceptions and experiences of higher education administrators of 4-year colleges in terms of the application of student data targeted for tracking and predicting retention? Efforts to answer the research question are further described in this chapter. This chapter includes the setting of this study as well as specific participant information. describe minimum requirements for participation. A brief description of the data collection process precedes the data analysis section that is the bulk of Chapter 4. A thematic coding approach was used via NVivo. This coding process is discussed in detail in the data analysis section. A brief summary of the chapter follows with a transition to Chapter 5.

Setting

Participants in this study were chosen from 4-year higher education institutions that had either a direct responsibility for retention initiatives or were indirect supervisors or committee members. Of the participants, four were from private and six were from public nonprofit 4-year colleges. Four participants had direct experience with identifying student data for retention initiatives, and it was in their job to do so as administrators. Three participants were also directly involved with identifying student data for retention initiatives via the nature of their direct student advising roles and specific student success data, analysis, and outcomes. Three participants were indirectly involved in identifying student data for retention initiatives via membership and supervision of a student service team that was tasked to do these responsibilities in either academics, student support, athletics.

This study was conducted during the COVID-19 pandemic. My focus was on perceptions and experiences of participants regarding data for student retention initiatives. Participants talked little about the pandemic and the influence of mandates on their retention initiatives. This could have been an unexpected effect to consider during data interpretation; however, during the inductive coding process, these items became irrelevant to the results, as participants did not relate any of the interview questions to be influenced by the pandemic.

Data Collection

The 10 semistructured interviews with participants currently employed in administrative higher education roles served as sources of data. Each participant had direct or indirect responsibilities for defining and selecting student data for retention initiatives at their 4-year U.S. institution (see Table 3).

Table 3

States Represented by Study Participants

Number of Participants	State
1	Indiana
1	Michigan
2	Missouri
2	Pennsylvania
4	Ohio

Each interview was manually coded for initial patterns in the interview data as well as researcher notes and memos during interviews. Interviews were conducted remotely and audio recorded and transcribed via the Google transcription tool. After receiving consent from each participant, they were assigned a participant number to safeguard confidentiality and privacy. Each participant engaged in one Zoom or Google Duo meeting that lasted 45 to 60 minutes. The format was dependent upon participant preferences given their preferred software platforms for virtual meetings. I encouraged each participant to schedule meetings at their convenience where they could be either in their own home or a private office if they chose their work environment. In doing so, each participant would have only those around them they felt comfortable with. Before the start of each interview, I reminded them of the consent form and meeting recording and transcriptions, and thanked them for their time and commitment. Once interviews were completed over the course of a 3-month period, I read each transcript thoroughly while listening to audio recordings to correct any grammatical or inaccurate transcriptions errors. There were no notable variations during this procedure. I then began the manual a priori coding process. I then uploaded data to NVivo 12 for data reorganization to begin data exploration. This process was the beginning of coding relevant information that would generate themes to answer the RQ.

Initially, the number of participants sought was at least 12. However, data saturation was reached after 10 participant interviews. Saturation occurred when no additional data were found that was different from the first nine participants. As I saw similar experiences and perceptions related to the RQ repeatedly, I became confident that data related to answering the RQ was saturated. During data collection, I began to see repeated patterns in transcripts during the sixth interview. However, in order to address diversity of data and to make certain that saturation was based on the widest range of data, , I continued with four more participants to confirm saturation.

Throughout the data collection process, the semistructured nature of the interview tool allowed participants to lead the discussion and provide open ended answers for their experiences and perceptions regarding the evolution of data mining at their institution. Further, the open ended semistructured interview tool also allowed the participants to describe their specific duties related to the retention initiatives and student variable selection and defining processes.

Data Analysis

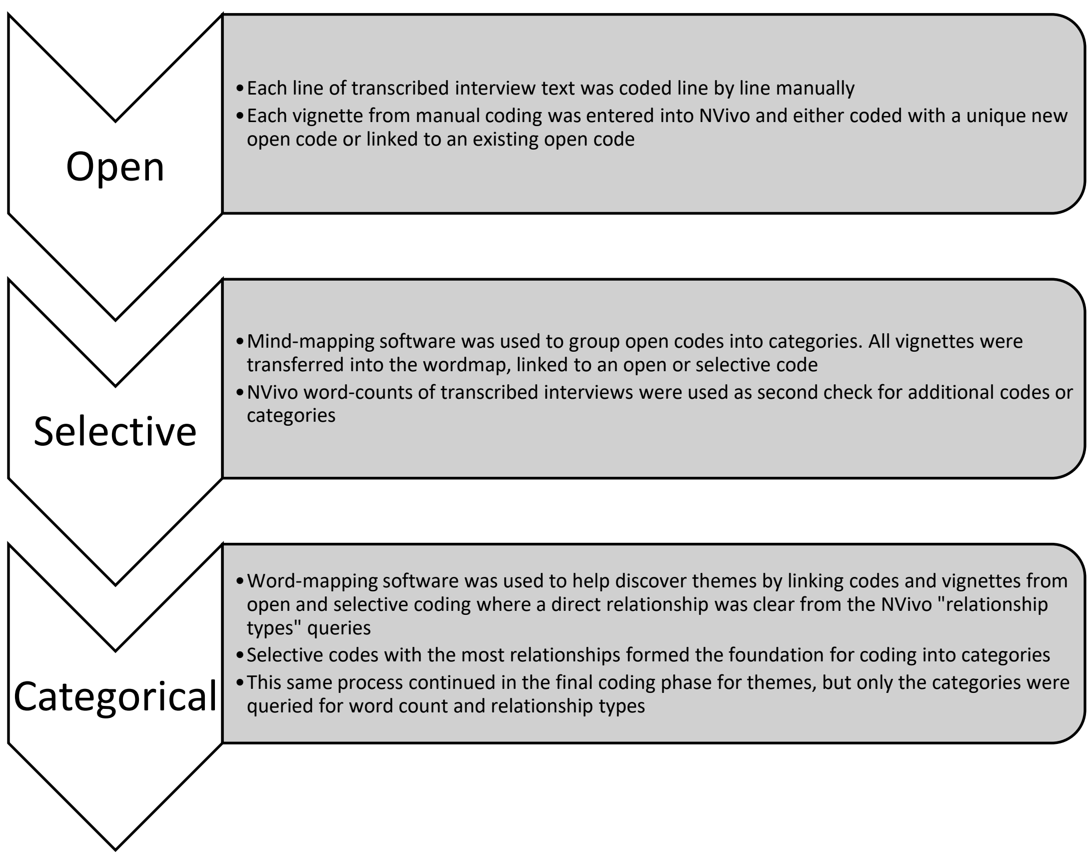
A framework analysis was conducted and consists of several stages such as familiarization, identifying a thematic framework, coding, charting, mapping and interpretation (Stahl & King, 2020). A framework analysis is used in qualitative research when a naturalistic approach to data gathering is sought and the researcher seeks to understand phenomena in context-specific settings. The real world setting allows the participants to be comfortable in the research process and the researcher does not attempt to manipulate the phenomenon of interest and only try to unveil the ultimate truth (Bochner, 2018).

Data analysis began with the initial a priori coding (see Appendix C) of audio transcripts. Each transcript was reviewed line-by-line for six a priori codes. Once initial a priori coding was complete, I began open coding. I completed line-by-line manual open coding of transcripts to determine additional codes found repeatedly throughout each transcript. Audio transcripts with completed a priori and open manual coding of all 10 interviews were then uploaded to NVivo 12. Each was loaded and labeled as a case file with designated participant confidential identifiers. Each case file was manually coded within NVivo to create a second coding process of interviews. This helped the analysis process remain consistent in terms of emphasizing key points during coding that were cross-checked with researcher notes and memos during the open coding process. This resulted in 811 initial codes initially. Some of the most common codes, found five or more times in transcripts were: not data informed, no communication among programs and departments, lack of defined processes for retention initiatives, student attributes changing from term to term, lack of leadership driving best practices for student retention, lack of knowledge of who is responsible for identifying student attributes and variables for research, faculty and staff frustration, lack of centralized data warehouse platform, lack of data mining knowledge, lack of people to gather data for student retention, reactive rather than proactive decisions, lack of internal-external resources for analytics software, and lack of transparency for student retention initiatives.

During the selective coding phase, I searched to find categories emerging from similarities in open codes. Using word-mapping and relationship types queries in the software, I took all the vignettes and the open codes and mapped them into a tree-map and word cloud. Diverging instances of the identified patterns and trends were noted from the narratives of the participants and they gave new meanings to my understandings of the text. Some coding patterns found most common, five or more times in the transcripts, in this selective coding process were: *inconsistent data tracking, no common data mining definitions, no common data mining process, decentralized student retention initiatives,* *decentralized data retrieval, manual raw data kept in excel and google docs, too much time to gather and analyze data,* and *decisions made before data can be presented.* Figure 2 includes the summary of the data and analysis process for a priori, open, selective, and categorical coding. Using NVivo 12 software, I continued with word-count queries and relationship or connection types cross checking tool as another means in discovering selective codes from the data.

Figure 2

Data Analysis Process



In analyzing the depth of codes, or the quantity of vignettes assigned to a group of codes, or grouping of open codes, selective codes emerged from the data. For the purposes of this study, the researcher defined depth as having 10 or more vignettes assigned to a code. Thematic coding resulted from the connections both within and across the open codes and selective codes. Connections across the selective codes were analyzed with the mind-map tool within NVivo. When building the mind-map, each time a vignette linked directly to a code, I reviewed that vignette for connections with other codes and each had a designated color assigned to it. If there was a connection, NVivo connected the codes with that designated color coded line. The selective codes with the most connections formed the start of thematic coding.

Emerging Selective Codes into Formed Categories

Inductive and comparative strategies endorsed by Merriam and Tisdell were used to analyze similar data revealed in multiple codes that grouped into categories, and then into final themes. The initial coding cycle of the interview transcripts resulted in 23 initial relationships from mind map coding. In subsequent reiterations my list of categories was narrowed to nine. I consolidated several items into similar threads following Saldaña's recommendations of sorting and shifting coded materials into categories, the relationship between variables, patterns, and themes. The clarity and depth shared in the interviews generated a total of 464 coded subdivisions during my analysis (Table 4). Discrepant cases that were found in the data were those that were misaligned from the majority of the interviewee results. Discrepant cases were set aside and used in a brief discussion in each themed area to be deliberated in the Results section of this chapter.

Table 4

Frequency of Codes to Categories and Subthemes

Categories/Subthemes from Coded Vignettes/ Segments Final Round	Total Word Frequency Relationships	Interview Transcript	Participant Segment Count	Researcher Notes	Count Total Segment Code
Siloed Data	79	A1	24	15	39
Siloed Communications	71	B2	29	11	40
Time Consuming	66	C3	36	18	54
Manual data retrieval	59	D4	33	13	46
No centralized data warehouse	53	E5	39	11	50
No common data language	42	F6	35	19	54
Inconsistent data practices	34	G7	26	17	43
Varied student attributes	31	H8	32	11	43
Partial data driven decisions	29	I9	27	21	48
		J10	35	12	47
Total:	464	Totals:	316	148	464

Results

In this section, I discussed the main themes associated with answering the research question and any subthemes related. The research question guiding this study was: What are the perceptions and experiences of higher education administrators of 4-year colleges in the application of student data targeted for tracking and predicting retention? Themes that emerged were:

Theme 1: There are no common data mining practices or definitions;

Theme 2: Student retention decisions are only partially driven by data; and

Theme 3: Data is siloed and subthemes are (a) manual data retrieval processes and (b) time consuming data analysis process.

Theme 1: No Common Data Mining Processes or Definitions

According to the perspectives shared by the college administrators interviewed for this study, there is frustration in understanding the data mining processes for student retention initiatives. Further, the college administrators were frustrated by the lack of a common language or definitions at their institution for the data analysis process and the variables used for research. The participants also shared that although there were common academic and administrative language that is understood by most faculty and staff, this did not translate over to the data collection, storage, and analysis that leads to results of unknown origin.

Regarding Theme 1, D4 stated:

> Honestly, I have no idea what student data are used for retention initiatives….the problem is that we have no common data language. The other problem is that no one seems to know how we get the data results or where they come from.

I9 said:

> This is a frustrating time for us because of COVID-19. We have to know what our students are thinking and how they are feeling. But defining the parameters for measuring this is just as difficult as understanding how to do it.

Participant F6 was frustrated with leaderships and in regard to Theme 1 stated: “Transparency shouldn’t be a privilege in student retention. We should have a common language and understanding for the process and where the data originates.”

Two discrepant cases in regard to Theme 1 came up in the data analysis process. C3 felt that defining a common language for gathering and presenting data for student retention was important, but not as important as trusting the leadership put in place to track and monitor student retention. C3 further stated:

> I have an important job and it matters to a great many people that we are driving best practice and student service delivery with data. However, they do not ask how we define the data or the outcomes. Faculty and staff just want to know what to do to retain students. It comes from trust.

J10 stated:

> Data for retention initiatives is going to vary for each institution as well as the definitions for the variables and research process. It is more important to focus on pulling the right variables and attributes to get the outcomes we need to drive our practice. That in and of itself is hard enough.

Theme 2: Student Retention Decisions are Only Partially Driven by Data

Most of the administrators interviewed expressed concerns of not being a data driven institution. This concern played out in multiple experiences that were shared during the interview process. These concerns were related to being reactive rather than proactive with student retention and leadership lacking explanation for policy changes. The participants also shared great frustration with leadership adding or removing services based upon what other institutions are doing or trends, rather than having a reliable data analytics structure for predictions related to student retention.

A1 spoke of these lack of data informed decisions at their institution and stated:

> We do not have a choice in high level student retention reporting. We have to have strong, reliable data for reporting to IPEDS and HLC accrediting. The

> department and program level data are hard to find, collect, and analyze to make decisions on student preferences for format delivery and types of services needed. We rely on some student survey outcomes that are around 15% participation, and the rest is gut instinct and results of many discussions and meetings.

B2 also shared concerns at their college on the lack of data informed decision making and the toll it has taken on retention rates. B2 stated:

> I know COVID-19 plays a factor in declining retention rates, but ours were falling long before this. We cannot make a data informed decision in one area like admissions and lack the wherewithal in other areas just as important, like student retention.

H8 shared more detail about the frustrations of higher education decision making downfalls. H8 stated:

> We are supposed to be here to help our students succeed. We cannot fail at this. But how are we supposed to help our students if we fail to help ourselves? We should see through the data outcomes lens, what are students need and what the level of need is so we can act appropriately. But, our institution continues to be impatient with data analysis and invests in poor time management, rash decisions, and lack of resources to influence positive change in student retention.

One discrepant case was noted. G7 stated:

> We are moving toward a data informed decision-making culture. It has taken years to do so, but we are less and less desiloed [sic] and more and more integrated with communication, data analysis, and working together for student

> retention efforts. Although we lack a centralized data warehouse, we make up for it in intentionality of our manual data retrieval processes.

Theme 3: Data is Siloed

All participant data resulted in solidarity on this third and final theme. Although there were discrepant cases in the subthemes, the misalignment was slight, but enough to discuss as discrepant. The college administrators viewed higher education in general as competitive based on fear. This fear is from lack of resources and a fickle climate for degree seeking consumers. The data analysis from the college administrators made clear that internal fear at individual institutions existed for the same reason and created the siloed effect. Each department and program have a solitary mission to grab all they can and seek the attention of Trustees and Executive leadership to survive, while subtly driving down the success of other departments and programs. Sharing data and integrating efforts to increase student success is not a priority, unless it serves to advance the success and presence of the department itself.

E5 said:

> The competition amongst ourselves makes my job difficult, if not impossible. We are siloed as it is and gathering data for student retention initiatives is like herding cats. Some programs will gladly give help as well as ask for help with deciphering data and choosing student data to research. Other programs will not budge and they assume that any data they gather belongs to them, but it belongs to our institution. This siloed mentality will eventually close our doors.

D4 said: “Retention initiatives would be much easier if I didn’t have to gather from 11 different islands. Each island has their own government and rules. None of them work together.”

H8 said: “Our customer is our student, bottom line. If that is not a good enough reason to come out of your fortified bunkers to share information and keep our doors open, then what will it take?”

A1 agreed and said:

> We have to be able to gather data and make decisions in unison. The internal communication breakdown and data corruption will only serve to hurt ourselves and our students. We have to coexist, and the common ground is institutional survival through student success and retention.

Subtheme A: Manual Data Retrieval Processes

Many of the participants described data collection and storage as a manual process held within Excel sheets and Google docs. The data is raw and not aggregated until someone needs to access an aggregate response to a question for driving practice or policy. There is then a continuation of this manual process through running PIV tables, formulas, and a series of cut and paste activities to try and understand the data and the variables that speak into it. There is a large margin of human error as well as inconsistent process and unreliable data outcomes.

D4 said:

> You cannot move the needle on retention if you do not know where the needle is. We do not have one haystack to find the needle, we have many haystacks. It

equates to grabbing hay handful by handful and potentially having to do it again and again because you missed a few and still cannot find the needle.

H8 said:

We are missing a lot of opportunities here and we need get caught up. Keeping data on spreadsheets in dozens of offices across the institution is not only a HIPPA violation in some cases, it is not best practice. Manually retrieving data from department to department reaps only muddied results. We need a better way.

Participant J10 in this study shared similar sentiments on this issue and stated:

Right now, in my job, I have to track 421 students' success. This is all on Excel spreadsheets and I have trained myself on how to run certain formulas and PIV tables to understand the needs of my students. There is not data analytics software and we all need it desperately.

However, G7 said:

We have a mix of some department level data analytics software but still rely upon some manual data processes. The software helps speed up the deciphering of raw data and decreases human error as long as the human conducts data input correctly. The need for manual processes may never go away. This may be a necessary inconvenience for the sake of cross checking if nothing else.

Subtheme B: Time Consuming Data Analysis Process

College administrator experiences have been described as not enough time to process data because it takes a lot of time to process data. My analysis of the transcripts gleaned perceptions that spoke of unrealistic expectations for data results in days that, in reality, take weeks to clean, organize, and decipher. Even the best of data analytics software takes hours to input data points, choose filters, and run reports. This can be an iterative process depending upon the software and the task at hand. But to input data into columns of Excel sheets and Google docs that require organizing, filtering, formulas. And PIV tables just to get started is a whole different stress on time and human capital.

E5said:

> There are days that I want to give up. So much time is invested in gathering sheets of data to organize, clean, and start to run PIV [sic]. Then someone changes the request or deadline in the slightest and panic ensues. It shouldn’t take days and days to get data analysis to work for us.

B2 stated:

> The time it takes for me to produce even the simplest of data requests, such as a course roster showing attendance concerns, takes a day or two. This is because it has to be cross checked with the registrar because the LMS and SIS do not talk to each other. I could have helped at least 6 to 10 students one on one in that time.

F6 said:

> There is not enough time in any given day as it is. The process to grabbing raw data from excel sheets and playing with filters and rows and columns is just exhausting. Part of the time issue is just from using the help function on Excel to learn how to do a filter or modify a PIV table. Our institution has to invest in analytics software. We need it for many reasons. But just to be able to give back hours upon hours of my time and that of my team would be invaluable.

I9 stated: "Time is not the issue, it is the lack of resources. Getting good data takes time, that's the nature of the beast. We have to do it right or it is not worth doing it at all."

This section went through the three themes of the study, with the third theme having two subthemes. Each area gave a description of any discrepant cases except for Theme 3. The rest of this chapter will speak to the trustworthiness of my study and then provide a brief summary.

Evidence of Trustworthiness

Trustworthiness

Trustworthiness in qualitative research must be demonstrated to show proper methods and rigor were used throughout the data collection and analysis process (Babchuk, 2017). Protocols in trustworthiness include demonstrating credibility, transferability, dependability, and confirmability (Amankwaa, 2016; Korstjens & Moser, 2018). I followed the guidelines provided by Walden University's Internal Review Board and the research recommendations shared in the literature from Chapter 3 to ensure I executed my study with rigor and transparency to the processes contained within it.

Credibility

Credibility is authenticated in this study by assuring the participant response was received as it was intended through member checking (Patton, 2014). I provided participants with the opportunity to restate their answers during the interview and amend the meaning of their statements during the interview if needed (Madill & Sullivan, 2018; Patton, 2014). During interviews I addressed vague responses with repeating questions in order to reflect participants statements back to them for clarification (Madill & Sullivan, 2018). There were instances where participants were unsure of the meaning of the interview question and I repeated the interview question by changing the tone or highlight certain words without changing the meaning.

The second credibility authentication method I used was reflexivity. Korstjen and Moser (2018) described this as the process of critical self-reflection about oneself as the researcher and one's biases, preferences, and presumptions as well as the relationship to the participants and how this relationship may affect their answers to questions. By journaling and taking notes throughout each interview, I monitored my own explicit and implicit assumptions and values in all phases of this study. Finally, confirm credibility in my study I used discrepant data findings in each theme described in this chapter. Negative or discrepant data is described by Patton (2014) as exceptions to the patterns found in the data. When discrepant data was found in participant transcripts, I reviewed and reflected from a cross checking perspective via interview recordings, researcher memos, and NVivo data queries. This is done to determine useful support of the study as well as responses not aligned to the final thematic results in order to show rigor and transparency.

Transferability

As stated in Chapter 3, transferability relates to the ability to transfer the results of the study to a population differing from the one used in the data collection (Amankwaa, 2016; Babchuk, 2017; Kallio et al., 2016). By providing this rich description of the participants, setting, sample size, the research process, and the findings (Korstjen &

Moser, 2018). The reader of this study can decide whether the findings are transferrable to their setting. The job of the researcher is providing as much context as possible so lens can be clear for the reader to see applicability to their setting or not (Arensdorf & Naylor-Tincknell, 2016).

Dependability

Dependability is necessary in a research study to show reliability of the data collection and the analysis (Amankwaa, 2016; Babchuk, 2017; Kallio et al., 2016), as stated in Chapter 3. For this study, audit trails are easily accessible in a few forms from the start of this research study to the development and reporting of the findings as needed to show transparency. Part of the audit trail used in this study was the a priori coding system (Appendix C) protocol used by the researcher for the interview questions and audio transcription as another means of cross-checking interview data of the participants with NVivo software. Finally, the handwritten reflexivity notes are accessible as well as the recordings of the participant interviews for review as needed (Silverman, 2016). I followed the specific stage by stage process from general note taking during participant interviews through reflexivity, use of the priori coding in the interview questions that were used during the data collection process through deductive coding and cross checking with the NVivo software (Feng & Behar-Horenstein, 2019).

Confirmability

As stated in Chapter 3, confirmability refers to objectivity or the ability of others to confirm findings (Stahl & King, 2020). Confirmability also refers to the researcher's transparency and documentation of processes (Korstjen & Moser, 2018; Nowell et al., 2017). I show confirmability in this study when I described the process used for data collection and analysis as suggested by Meadows (2003). I provided a detailed description of the sequence for data collection, coding, and analysis to deliver a clear and well-defined accountability for the process as shown throughout this chapter.

Transparency can be defined as “the degree of detail and disclosure about the specific steps, decisions, and judgment calls made during a scientific study” (O’Kane et al., 2021, p 105). I provided transparency to the data collection and analysis process by discussing the levels of queries used within NVivo 12 software. Abu (2016) stated that this confirms a level of credibility for the researcher that provides trustworthiness of the data results when using an analytics software platform. This process was described in detail in this chapter to provide the transparency of the data analysis development that yielded the main themes and results of the study as seen in Table 4 and Figures 3, 4, and 5.

Trustworthiness in This Study

Trustworthiness, the central concept by which to judge the quality of interpretive qualitative research is enhanced by demonstrating that researchers understand their context and data (credibility), showing consistency and lack of bias in data analysis (confirmability), providing enough detail for possible replication (dependability), and allowing for assessment of a study’s outcomes in relation to other contexts is transferability (Korstjen & Moser, 2018; Lichtman, 2017; O’Kane, et al., 2021; Patton, 2014). Maher et al. (2018) stated that NVivo software maximizes researcher data interaction in a variety of modalities that ensures the analysis process is rigorous and productive. They further stated that reflection on an authors' research analysis process, combined with consultation with the literature, would suggest digital analysis software packages such as NVivo do not fully scaffold the analysis process but provide excellent data management and retrieval facilities that support analysis and write-up. Further, Bonello and Meehan (2019) agreed and stated that the NVivo 12 software platform was intuitive enough to drive intentional queries on the data while showing the trail of breadcrumbs for researcher credibility and trustworthy results in qualitative study (p. 490).

Another point in achieving trustworthiness for this study was use of a thematic coding process. Thematic analysis provides a highly flexible approach that can be modified for the needs of many studies, providing a rich and detailed, yet complex account of data (Nowell et al., 2017). Thematic analysis is a particularly good choice for those researchers early in their career and does not require the detailed theoretical and technological knowledge of other qualitative approaches, it offers a more accessible form of analysis (Tobin & Begley, 2004). Thematic analysis provides a decision trail, stated White et al. (2012), that can be shown and presented via narrative or visual display that enhances the rigor of study with thematic coding process.

Summary

The research question driving this study was: What are the perceptions and experiences of higher education administrators of 4-year colleges in the application of student data targeted for tracking and predicting retention? Three main themes emerged from the inductive coding process driven by the NVivo 12 software platform. The documents uploaded into the NVivo software for the coding process were the interview transcripts with initial manual coding completed and my notes and memos written during the participant interviews. In deciphering and coding the participants' experiences and perceptions, the first theme that emerged is that there is no common data mining definitions nor language for understanding the process for student variable identification in retention initiatives at each institution. The third theme that emerged from the participants' perceptions and experiences is that there is a manual process due to siloed institutional data.

This third theme also contained two subthemes. The first subtheme was the manual process for siloed data this further causes challenges in data result turnaround time. The process to retrieve raw data and analyze in a timely manner requires many resources that institutions do not have to be a data driven college. The second subtheme was retention initiatives can only be data driven at a minimal level because of the manual processes across an institution. These themes and subthemes will be further deliberated in Chapter 5 in the final discussion, conclusions, and recommendations regarding the results of this study.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this basic qualitative study was to explore perceptions and experiences of administrators of 4-year colleges in terms of their application of student data for tracking and predicting retention. This study could potentially fill a gap in the literature regarding tracking and predicting processes needed for college retention initiatives. I conducted interviews with retention administrators at 4-year U.S. colleges to obtain their experiences and perceptions regarding student data applications for retention initiatives at their institutions. I manually coded data before uploading the documents into NVivo 12 for further coding. I reported findings by discussing main themes that emerged. The themes that emerged for answering the RQ were, that no common data mining practices or definitions existed, and that student retention decisions are only partially driven by data, and siloed data is prominent and problematic. The third theme, siloed data, had two subthemes that were, manual data retrieval is problematic and this further creates time-consuming data analysis processes. This chapter includes interpretations of findings as well as limitations of this study. Before concluding this chapter, I include a brief discussion of recommendations and implications of this study.

Interpretation of the Findings

Interview data were used to provide answers to the RQ for this study. Themes aligned with peer-reviewed literature regarding retention initiatives in higher education. In this section, I present interpretations of findings for this study and describe how it connects to, confirms, and extends what has been found in existing literature.

Theme 1: No Common Data Mining Practices or Definitions

A need in higher education data practices is for a common set of definitions to inform a general understanding for administrators of data mining practices was a theme identified in this study. This theme is supported by findings from previous literature and research that showed a need for higher education to start with basic knowledge of data mining processes that should be informed by a common set of definitions and policy to drive research initiatives. Having a set of common data mining definitions to drive student variable identification for retention initiatives is integral to supporting results that confirm data transparency in practice. Institutions frequently begin data mining practices out of order and have a difficult time with faculty buy-in and gaining trust of staff without first implementing common agreed upon data mining definitions that inform and confirm processes for analyzing and presenting results (Chaurasia et al., 2018; Gagliardi et al., 2018).

Knowledge of basic data mining terminology was not widely known by the participants in this study. Such as the Gandomi and Haider three V construct (2015) that speaks to the process of data being broken down into prescriptive, predictive, and descriptive parts and allows decision-makers to see patterns and trends from past outcomes. Torrecilla and Romo (2018) said common data mining processes are collected in very different ways, that can be a manual excel sheet process or via the use of software systems that calculate data through a filtering and specific search language for analysis. Kwon et al. (2014) said to maintain quality of data, institution-wide data mining definitions must be in place in higher education to underpin practices and processes. Lack of participant knowledge as well as their peer administrators was noted as also preventing colleges from successfully applying student data in retention initiatives.

Theme 2: Student Retention Decisions are Only Partially Driven by Data

Many participants perceived their institution to be inept in terms of data-driven decision making and this primes institutional leadership to making knee-jerk reactions rather than being proactive. New processes should be considered for outcome-based education including data administrators to take an intentional look at student data within departmental audits to reveal student success measurements and tracking to fuel data-driven decision making involving retention. Also, many institutions do not have a culture of data-based decision making, and therefore identification of student data to assess learning as well as overall retention is problematic I identifying those students who retain and why (Chaurasia et al., 2018).

Participants said inconsistency in data tracking and unknown origins of data affects institutional decision-makers in terms of having enlightened institutional data tracking policies and processes adopted for student success. Niebel et al. (2019) said data-informed decision-making practices quickly yield benefits to higher education institution through increased retention, financial returns, and satisfaction of customers.

Theme 3: Siloed Data

Participants in this study stated that a big problem at their institutions was siloed data. Findings in this study indicated that a point of frustration was a lack of a common or centralized system for storing and analyzing data. Matsebula and Mnkandla (2017) said the absence of an appropriate infrastructure for data mining feeds a culture of separated and individualized data practices, which leads to data tracking failures to support decision-making that influences student retention and institutional revenue in many facets of student success in higher education such in academics and social connectedness. Avella et al. (2016) said data systems that rely upon siloed data and manual practices for data analysis have proven to be ineffective for time management and tend to be riddled with human error in terms of tracking student retention in higher learning institutions. Williamson (2017) said ethical issues in data storage and student information protection are an ongoing concern. He continued and stated that retention data should be housed in a centralized data warehouse, and responsibility for its use and application should be widely dispersed with proper training and accountability.

Subtheme A: Manual Data Retrieval Processes

Participant data showed frustrations with manual data retrieval processes that come from siloed data practices. participants perceived their institutions as struggling to make data-informed decisions, and manual processes for retrieving siloed data was one of those reasons. Tsai et al. (2015) said management, processing, and application of raw student data cannot be accomplished using simple Excel sheet formulas that were once considered traditional. Collection and analysis processes for identification of variables in retention requires a more sophisticated approach then the use of manual paper processes and siloed data.

Data results from interviews showed a consistent concern for ethical issues involving data being kept in spreadsheets and files within each department and program, which leads to ethical issues involving protection of student data. Lacerenza et al. (2018)

said participation in decision-making to promote healthy institutional climates begins with collecting unbiased and protected student data. Lacerenza et al. said successful teams produce desired outcomes with clean and safe data variables using demonstrated and effective processes. Team development interventions are relevant in terms of institutional survival, but this is contingent upon adherence to data policy and ethical practices that protect student data.

Subtheme B: Time Consuming Data Analysis Processes

The second subtheme that emerged from the third theme was the time-consuming process for data analysis that occurs with siloed data. Participants shared that this is a primary barrier to successful data informed decision making in siloed data practices. Many of the interviewees stated that decisions must be made whether there is data or not. But when it takes days or even weeks to track, collect, analyze, and produce an aggregated result and infographic(s), there are just too many decisions that need to move forward. Unfortunately, these decisions are forced to be made as a best educated guess. The hope is that the data that follows confirms the decision. Participants stated that they see this type of decision-making being done from an institutional level on down to course level because data is not readily available.

Higher education administrators who value introducing new methods of thinking as well as a means of data-informed practice are typically met with barriers (Cope & Kalantzis, 2016). These barriers are associated with the time-consuming task of gathering, analyzing, and applying data that is siloed and decentralized. Hadwater et al. (2018) agreed and stated that the barriers that have contributed to the slow adoption of data mining efforts are institutional policies that do not support a centralized and time efficient data mining system. This lack of support in policy and practice ultimately depletes the efforts needed for student success and institutional revenue (Baer & Norris, 2016).

Limitations of the Study

As the sole researcher of this study, I was responsible for collecting, coding, analyzing, and interpreting the findings. This can create a limitation of this study in that I am a partial insider researcher because I have a similar professional role to the participants who the author interviewed. However, I am removed from the community of which each participant was a part (Fleming, 2018). I did not intentionally make any decisions to influence the participant interviews. However, I do have a similar role and knowledge as the participants and may have inadvertently influenced participant responses. But as an insider, I was able to speak the jargon and pedagogy with which participants may be familiar, and this allowed for a comfortability to retrieve honest and open responses.

I followed Walden University's Institutional Review Board recommendations and ethical guidelines and used several methods to mitigate my bias and any influence over this study (Butler, 2016; Cresswell, 2013; Shufutinsky 2020). I kept detailed notes and memos during the data collection process to review any potential biases I may have had regarding the participant interview process and data collection, and this provided a tool for me to engage in self-reflection. I also used reflexivity to evaluate each interaction with participants while maintain a professional boundary appropriate as the researcher.

Recommendations

I have three recommendations for further research. The first recommendation is to conduct a study that specifically addresses the experiences and perceptions of administrators in higher education that can speak to the data culture of their institution. This study paralleled the topic, but participant perceptions and experiences were inconsistent as to the data culture in their institutions. Administrator perceptions of analytics and data mining tends to contribute to its acceptance and use as a medium for generating variables for institutional research (Chaurasia et al., 2018). Andrews and Lemons (2015) stated that for a decision-making culture to exist and to be based upon data evidence, this practice cannot be at the institutional level alone. The data culture needs to permeate to staff and faculty who are responsible for the day-to-day services with students. For example, faculty that continue to make decisions based on personal experiences rather than data need to be brought into the data culture as they have the most direct knowledge and experience with students (Andres & Lemons, 2017). A good place to start in driving efficacious data mining in higher education would be to first gauge if the culture is ripe for such tasks.

A second recommendation would be to quantitatively conduct a study on the level and type of siloed data that exists in higher education and what would it take to centralize these efforts. The data results of this study showed that siloed data is problematic, so much so, that it was a main theme. This theme of siloed data contained two subthemes that stated barriers in time management and manual data processes still in place. Additional study to take a deeper dive into siloed data and the use of manual tracking systems would benefit higher education best practices (Avella, et al., 2016). This knowledge is needed so that siloed data practices that have proven to be ineffective in resolving student retention in higher learning institutions are more widely researched and provide guidance for resolution (Matsebula & Mnkandla, 2017). Williamson (2017) acknowledged this and stated that educational data science needs predictive measures for retention but the level of expertise, manual tracking, and available workforce can be a barrier. Williamson added that retention data should be housed as a centralized data warehouse, but the responsibility and application of desiloed data should be widely dispersed with proper training.

My final recommendation would be to address the ethical concerns related to student data in higher education. Within the context of this study, participants expressed concerns for student data being on every faculty desk across campus as a result of siloed data practices. Although this study did address the barriers to siloed data in higher education as it relates to retention initiatives, the topic of data ethics was beyond the scope of the stated problem and purpose. So, it is recommended that further study take place to address this. The nonexistence of the students' voices regarding the use of data mining has presented challenges related to the acceptability of student attributes used for institutional research (Roberts, et al., 2016). Data analysis in higher education related to students has been comprised by way of using demographic details, enrollment survey results, student course assessment, and the academic performance of students, among others (de Freitas et al., 2015). Ethical perspective is needed in higher education research to consider student participation in decision making to promote a healthy institutional climate that serves and benefits all stakeholders.

Implications

By gathering the experiences and perceptions of administrators in this study and how they see their institution through the student retention lens I learned that this gives a voice to those struggling with organizational change in data culture. Positive organizational change occurs when individuals achieve their goals and have influence on others. In this way, the findings can influence those administrators wanting change in their institution for data mining practices in student success by improving policy and practice by beginning practices to desilo data, improving data informed decisions making, and creating a common language for practices when using student data in retention initiatives. This methodological change in practice can ultimately improve the goal achievement at the organizational level as well.

Higher education accreditation bodies and funders require data-informed results to show increasing progress each year. Organizational change can be influenced by the change in methods of practice. This study provides understanding of both the barriers and opportunities to begin successful data mining methods for practice and policy change in higher education that can further influence organizational change. Implications for change in methods of practice for data mining would first and foremost be an increase in student success and institutional revenue by incorporating the participant data into multi-level data informed decision making. Successful achievement of institutional goals will increase the viability of an institution to accreditors and the surrounding community. The key recommendations from this study that can influence social change on organizational and societal levels in higher education, by having open discussion to define common processes for data mining that increase trust and transparency in retention initiatives. This can be a positive motivator for organization change that also meets the societal expectations for data informed results in higher education.

The findings of this study showed that the Gandomi and Haider Three V Construct (2015) and Attarran et al. (2018) model of analytics used as the conceptual framework were not widely understood by the participants. The conceptual framework was successful in providing a common language and process that are considered basic and integral to any data mining efforts in business and education (Baker & Siemens, 2014; Sivarajah et al. 2017; Williamson, 2017). However, during data collection it was revealed that the participants knew little about this common process and language. This implicates that administrators are either being hired with little or no expertise for what is expected given their title and job description, or that data mining training efforts are needed.

Although the participants were all from 4-year colleges, the results can be transferrable to most higher education institutions that struggle with siloed data pools, little or no data mining processes, and need to increase data informed decision making. By reviewing methods of practice at varying levels of an institution, the findings of this study can inform the readers of main themes for improving performance in data mining initiatives in retention. One of the salient points from this study is to desilo data from departments and programs as much as possible to centralize the data mining process and protect student data. This is both integral to organizational and societal change that will further influence what an institution brings to the table for student success and how they are viewed by accreditors.

Conclusion

This study explored the perceptions and experiences of administrators of 4-year colleges in applying student data for tracking and predicting retention. Three themes emerged that can inform gaps in practice that have been noted in previous research literature. These gaps in practice have been barriers to student success and institutional revenue. The lack of common process and definitions for data mining practices accompanies a lack of transparency and distrust from staff and faculty. By making known what the processes are for identifying student data, who is responsible, and defining a common language for those processes, college administrators can open possibilities for organizational change and success. Improved understanding brought about through this study can be a first step in productive data mining practices for student success and retention initiatives. Centralizing data or assigning data responsibilities in a designated department can increase data productivity and data-informed decision making for institutions of higher education. Manual data entry and tracking practices from excel sheets and google docs are devices of the past. The outcomes of this study show that higher education administrators want efficiency and intentionality from data driven decisions. With increasing requirements for higher education institutions to produce reliable data results, time is of the essence. The time has passed for higher education to simply do what has always been done.

By giving a voice to those struggling with organizational change in regards to data culture, this provided an understanding of both the barriers and opportunities to begin successful data mining methods for practice and policy change. This change will influence higher education data mining practices organizationally speaking that can further influence community and social change that meets their expectations for data informed results in higher education to show student success and institutional stability. This can be accomplished in three integrated steps. The first is to influence organizational change through methods of practice. This study provides understanding of both the barriers and opportunities to begin successful data mining for updating methods for practice and policy change in higher education that can further influence organizational change. Implications for change in methods of practice for data mining would first and foremost be the understanding of common data mining language and practice that would yield an increase in student success and institutional revenue by incorporating the participant data into multi-level data informed decision making.

Organizations change follows when positive change occurs in updating methods of practice when individuals achieve their goals and have influence on others. In this way, the findings can influence those administrators wanting change in their institution for data mining practices in student success by improving policy and practice by beginning practices to desilo data, improving data informed decisions making, and creating a common language for practices when using student variables in retention initiatives.

Societal change follows when organizational change aligns to higher education accreditation bodies and funders data-informed requirements show increasing progress each year. Organizational change can be influenced by the change in methods of practice. Successful achievement of institutional goals will increase the viability of an institution to accreditors and the surrounding community. The key recommendations from this study that can influence social change on organizational and societal levels in higher education, by having open discussion to define common processes for data mining that increase trust and transparency in retention initiatives. This can be a positive motivator for organization change that also meets the societal expectations for data informed results in higher education. The need to desilo data from departments and programs, as well as drive the institutional culture with data informed decision makers, will yield a foundation of common language and practice in data mining and the ability to focus on the success of both students and institutions.

References

Albalowi, A., & A Alhamed, A. (2017, December 7). *Big data and learning analytics in higher education: Demystifying variety, acquisition, storage, NLP and analytics*. https://doi.org/10.1109/ICBDAA.2017.8284118

Alsharari, N.M., & Alshurideh, M.T. (2020). Student retention in higher education: The role of creativity, emotional intelligence and learner autonomy. *International Journal of Educational Management, Vol. #?*(Issue #?), p. ##-##? https://doi.org/10.1108/IJEM-12-2019-0421

Amankwaa, L. (2016). Creating protocols for trustworthiness in qualitative research. *Journal of Cultural Diversity*, *23*(3), 121-127. https://www.researchgate.net/publication/324804792_CREATING_PROTOCOLS_FOR_TRUSTWORTHINESS_IN_QUALITATIVE_RESEARCH

Andrews, T., & Lemons, P. (2015). It's personal: Biology instructors prioritize personal evidence over empirical evidence in teaching decisions. *CBE—Life Sciences Education, 14*(1), 1-18. https://doi.org/10.1187/cbe.14-05-0084

Arensdorf, J., & Naylor-Tincknell, J. (2016). Beyond the traditional retention data: A qualitative study of the social benefits of living learning communities. *Learning Communities: Research & Practice, Vol. #?*(Issue #?), p. ##-##?. https://eric.ed.gov/?id=EJ1112861

Attaran, M., Stark, J., & Stotler, D. (2018). Opportunities and challenges for big data analytics in U.S. higher education: A conceptual model for implementation. *Industry and Higher Education*, *32*(3), 169-182.

https://doi.org/10.1177/0950422218770937

Avella, J. T., Kebritchi, M., Nunn, S. G., & Kanai, T. (2016). Learning analytics methods, benefits, and challenges in higher education: A systematic literature review. *Online Learning*, *20*(2), 13-29. Online Learning 20.2 Full-Issue pdf.pdf (ed.gov)

Babchuk, W. A. (2017). Qualitative research: A guide to design and implementation (4th ed.). *Adult Education Quarterly*, *67*(1), 71–73. https://doi.org/10.1177/0741713616671930

Baer, L. L., & Norris, D. M. (2016). A call to action for student success analytics. *Planning for Higher Education*, *44*(4), 1-10. A call to action for student success analytics. *Planning for Higher Education*, *44*(4), 1-10. DATA2018_PRIMER_DOWNLOAD.pdf (naspa.org)

Baker, R.S., & Siemens, G. (2014). Educational data mining and learning analytics. In K. Sawyer (ed.), *Cambridge handbook of the learning sciences* (2nd ed., pp. 253-274). Cambridge University Press. Educational Data Mining and Learning Analytics: Applications to Constructionist Research | SpringerLink

Barbour, R. (2014). *Introducing qualitative research: A student's guide*. SAGE Publications. Introducing Qualitative Research: A Student's Guide - SAGE Research Methods (waldenulibrary.org)

Barratt, M. J., Ferris, J. A., & Lenton, S. (2015). Hidden populations, online purposive sampling, and external validity: Taking off the blindfold. *Field Methods*, *27*(1), 3-21. https://doi.org/10.1177/1525822X14526838

Bashir, M., Afzal, M.T., & Azeem, M. (2008). Reliability and validity of qualitative and operational research paradigm. *Pakistan Journal of Statistics and Operation Research*, *1*(1), 35-45. https://doi.org/10.18187/pjsor.v4i1.59

Bochner, A. (2018). Unfurling rigor: On continuity and change in qualitative inquiry. *Qualitative Inquiry*, *24*(6), 359-368. https://doi.org/10.1177/1077800417727766

Bomatpalli, T. (2013). Significance of big data and analytics in higher education. *International Journal of Computer Applications*, *68*, 21-23. https://doi.org/10.5120/11648-7142

Bonello, M. & Meehan, B. (2019). Transparency and coherence in a doctoral study case analysis: Reflecting on the use of NVivo within a 'framework' approach. *The Qualitative Report*, *24*(3), 483-498 https://www.proquest.com/openview/5bc7bedc8740d7875375b49d80688e5c/1?pq-origsite=gscholar&cbl=55152

Bradley, E. H., An, M.-W., & Fox, E. (2020). Reopening colleges during the Coronavirus disease 2019 (COVID-19) pandemic—One size does not fit all. *JAMA Network Open*, *3*(7), e2017838-e2017838. https://doi.org/10.1001/jamanetworkopen.2020.17838

Braxton, J. M. (2019). Leaving college: Rethinking the causes and cures of student attrition by Vincent Tinto (Review). *Journal of College Student Development*, *60*(1), 129-134. https://doi.org/10.1353/csd.2019.0012

Bughin, J. (2016). Big data, big bang? *Journal of Big Data*, *3*(1), 2. https://doi.org/10.1186/s40537-015-0014-3

Busteed, B. (2016). Welcome to the exit era of higher education. *Gallup*. https://news.gallup.com/opinion/gallup/199304/welcome-exit-era-higher-education.aspx

Butler, J. L. (2016). Rediscovering Husserl: Perspectives on the epoche and the reductions. *The Qualitative Report*, 21(11), 2033-2043. Rediscovering Husserl: Perspectives on the Epoché and the Reductions (nova.edu)

Castillo-Montoya, M. (2016). Preparing for interview research: The interview protocol refinement framework. *The Qualitative Report*, 21(5), 811-831. Retrieved from http://nsuworks.nova.edu/tqr/vol21/iss5/2

Centers for Disease Control and Prevention. (2020). Coronavirus Disease 2019 (COVID-19). Prevention & treatment. Centers for Disease Control and Prevention. https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/prevention.html.

Chaurasia, S. S., & Frieda Rosin, A. (2017). From Big Data to Big Impact: Analytics for teaching and learning in higher education. *Industrial and Commercial Training*, *49*(7/8), 321–328. https://doi.org/10.1108/ICT-10-2016-0069

Chaurasia, S. S., Kodwani, D., Lachhwani, H., & Ketkar, M. A. (2018). Big data academic and learning analytics: Connecting the dots for academic excellence in higher education. *International Journal of Educational Management*, *32*(6), 1099–1117. https://doi.org/10.1108/IJEM-08-2017-0199

Chaurasia, S. S., & Rosin, A. F. (2017). From Big Data to Big Impact: Analytics for teaching and learning in higher education. *Industrial and Commercial Training*.

https://doi.org/10.1108/ICT-10-2016-0069

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, *36*(4), 1165–1188. JSTOR. https://doi.org/10.2307/41703503

Conrad, C. F., & Wilson, R. F. (1985). *Academic Program Reviews: Institutional Approaches, Expectations, and Controversies. ASHE-ERIC Higher Education Report No. 5, 1985*. Association for the Study of Higher Education, Publications Department, Washington, DC. https://eric.ed.gov/?id=ED264806.

Cope, B., & Kalantzis. M. (2016). Big Data Comes to School: Implications for Learning, Assessment, and Research. *AERA Open* 2(2). https://doi.org/10.1177/2332858416641907.

Creswell, J. W. (2013). *Qualitative inquiry and research design: Choosing among five approaches.* Thousand Oaks, CA: Sage

Creswell, J. W., & Poth, C. (2016). *Qualitative Inquiry and Research Design: Choosing Among Five Approaches*. SAGE Publications.

Crotty, M. (1998). *The Foundations of Social Research.* London: Sage.

Daniel, B. (2015). Big Data and analytics in higher education: Opportunities and challenges. *British Journal of Educational Technology*, *46*(5), 904–920. https://doi.org/10.1111/bjet.12230

Davidson, W. B., Beck, H., & Grisaffe, D. B. (2015). Increasing the institutional commitment of college students: Enhanced measurement and test of a nomological model. *Journal of College Student Retention: Research, Theory &*

Practice 17 (2): 162–85. https://doi.org/10.1177/1521025115578230.

DeCarlo, M. (2018). 13.2 Qualitative interview techniques. *Scientific Inquiry in Social Work*. (Chap 13). Pressbooks. https://scientificinquiryinsocialwork.pressbooks.com/chapter/13-2-qualitative-interview-techniques/.

de Freitas, S., Gibson, D., Du Plessis, C., Halloran, P., Williams, E., Ambrose, M., Dunwell, I., & Arnab, S. (2016). Foundations of Dynamic Learning Analytics: Using University Student Data to Increase Retention. *British Journal of Educational Technology*, *46*(6), 1175–1188. Foundations of dynamic learning analytics: Using university student data to increase retention - Freitas - 2015 - British Journal of Educational Technology - Wiley Online Library

Dewberry, C., & Jackson, D. (2018). An application of the theory of planned behavior to student retention. *Journal of Vocational Behavior* 107, 100–110. https://doi.org/10.1016/j.jvb.2018.03.005.

Ekowo, M., & Palmer, I. (2016) The promise and peril of predictive analytics in higher education: A landscape analysis. *New America*. https://eric.ed.gov/?id=ED570869.

Elgendy, N., & Elragal, A. (2016). Big Data Analytics in Support of the Decision Making Process. *Procedia Computer Science*, *100*, 1071–1084. https://doi.org/10.1016/j.procs.2016.09.251

Elhassan Ali, F. A., & Klett, F. (2018). Learning Analytics in Higher Education—The Path Toward Educational Management Intelligent Systems. *2018 11th*

International Conference on Developments in ESystems Engineering (DeSE), 244–249. https://doi.org/10.1109/DeSE.2018.00050

Elnozahy, W. A., El Khayat, G.A., Cheniti-Belcadhi, L., &Said, B. (January 1, 2019). Question Answering System to Support University Students' Orientation, Recruitment and Retention. *Procedia Computer Science,* CENTERIS 2019 - International Conference on ENTERprise Information Systems / ProjMAN 2019 - International Conference on Project MANagement. 164: 56–63. https://doi.org/10.1016/j.procs.2019.12.154.

Etikan, I. (2016). Comparison of Convenience Sampling and Purposive Sampling. *American Journal of Theoretical and Applied Statistics*, *5*, 1. https://doi.org/10.11648/j.ajtas.20160501.11

Feng, X., & Behar-Horenstein, L. (2019). Maximizing NVivo utilities to analyze open-ended responses. *The Qualitative Report*, *24*(3), 563-571. https://nsuworks.nova.edu/tqr/vol24/iss3/11

Finlay, L. (2013). Unfolding the phenomenological research process: Iterative stages of seeing afresh. *Journal of Humanistic Psychology* 53(2): 172–201. https://doi.org/10.1177/0022167812453877.

Gagliardi, J., Parnell, A., & Carpenter-Hubin, J. (2018). The analytics revolution in higher education. *Change: The Magazine of Higher Learning*, *50*(2), 22–29. https://doi.org/10.1080/00091383.2018.1483174

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, *35*(2), 137–144.

https://doi.org/10.1016/j.ijinfomgt.2014.10.007

Ganotice, F. A., King, R. B. (2014). Social influences on students' academic engagement and science achievement. *Psychological Studies* 59 (1), 30–35. https://doi.org/10.1007/s12646-013-0215-9.

García-Ros, R., Pérez-González, F., Cavas-Martínez, F., & Tomás, J. M. (2019). Effects of pre-college variables and first-year engineering students' experiences on academic achievement and retention: A structural model. *International Journal of Technology & Design Education* 29 (4), 915–28. https://doi.org/10.1007/s10798-018-9466-z.

Glesne, C. (2016). Becoming qualitative researchers: An introduction, 5th Edition. In *Pearson*. Pearson.

Gordon, R. (2020). *A basic qualitative research study: How marginalized students' ability to succeed is impacted during freshman and sophomore years in college.* [Thesis, Concordia University, St. Paul]. Retrieved from https://digitalcommons.csp.edu/cup_commons_grad_edd/183

Griffiths, A. (2017). Forecasting failure: Assessing risks to quality assurance in higher education using machine learning [PhD Thesis]. King's College London. British Library EThOS: Forecasting failure : assessing risks to quality assurance in higher education using machine learning (bl.uk)

Guetterman, T. C. (2017). Descriptions of sampling practices within five approaches to qualitative research in education and the health sciences. *Forum Qualitative Sozialforschung / Forum: Qualitative Social Research, 16*(2).

https://doi.org/10.17169/fqs-16.2.2290

Hadwer, A. A., Gillis, D., & Rezania, D. (2019). Big data analytics for higher education in the cloud era. *2019 IEEE 4th International Conference on Big Data Analytics (ICBDA)*, 203–207. https://doi.org/10.1109/ICBDA.2019.8713257

Harackiewicz, J. M., & Priniski, S. J. (2018). Improving student outcomes in higher education: The science of targeted intervention. *ANNUAL REVIEW OF PSYCHOLOGY, VOL 69*, *69*, 409–435. https://doi.org/10.1146/annurev-psych-122216-011725

Heflin, H., Shewmaker, J., & Nguyen, J. (2017). Impact of mobile technology on student attitudes, engagement, and learning. *Computers & Education*, *107*, 91–99. Impact of mobile technology on student attitudes, engagement, and learning - ScienceDirect (waldenulibrary.org)

Heiner, C., Heffernan, N., & Barnes, T. (July, 2007). Educational data mining workshop. Supplementary Proceedings of the 13th International Conference of Artificial Intelligence in Education. Marina del Rey, CA. USA 10.1.1.66.1441.pdf (educationaldatamining.org)

Henke, N., Puri, A., & Saleh, T. (2020). *Accelerating Analytics to Navigate COVID-19 and the Next Normal*. McKinsey & Company. accelerating-analytics-to-navigate-covid-19.pdf (mckinsey.com)

Hora, M. T., Bouwma-Gearhart, J., & Park, H.J. (2017). Data driven decision-making in the era of accountability: Fostering faculty data cultures for learning. *The Review of Higher Education* 40 (3), 391–426. https://doi.org/10.1353/rhe.2017.0013.

Hubler, S. (2020, August 15). As colleges move classes online, families rebel against the cost. *The New York Times*. https://www.nytimes.com/2020/08/15/us/covid-college-tuition.html

Huda, M., Maseleno, A., Atmotiyoso, A., Siregar, M., Ahmad, R., Jasmi, K., & Muhamad, N. (2018). Big data emerging technology: Insights into innovative environment for online learning resources. *International Journal of Emerging Technologies in Learning (IJET)* 13 (1), 23–36. (PDF) Big Data Emerging Technology: Insights into Innovative Environment for Online Learning Resources (researchgate.net)

Huselid, M., & Minbaeva, D. (2019). In Press: Sage Handbook of Human Resource Management (2nd edition), Wilkinson, A., Bacon, Lepak, L., & Snell, S. (Eds.). SAGE Reference - The SAGE Handbook of Human Resource Management (sagepub.com)

Kallio, H., Pietilä, A.-M., Johnson, M., & Kangasniemi, M. (2016). Systematic methodological review: Developing a framework for a qualitative semi-structured interview guide. *Journal of Advanced Nursing*, *72*(12), 2954–2965. https//doi.org/10.1111/jan.13031

Kivunja, C., & Kuyini, A. B. (2017). Understanding and applying research paradigms in educational contexts. *International Journal of Higher Education*, *6*(5), 26. https://doi.org/10.5430/ijhe.v6n5p26

Klimek, J. & Klimek, J.A. (2020). IT and data mining in decision-making in the organization. Education management in the culture of late modernity. *Procedia*

Computer Science 176: 1990–99. https://doi.org/10.1016/j.procs.2020.09.235.

Knapp, M. S. (2017). The practice of designing qualitative research on educational leadership: Notes for emerging scholars and practitioner-scholars. *Journal of Research on Leadership Education* 12(1): 26–50. https://doi.org/10.1177/1942775116647365.

Korstjens, I., & Moser, A. (2018). Series: Practical guidance to qualitative research. Part 4: Trustworthiness and publishing. *European Journal of General Practice*, *24*(1), 120–124. https://doi.org/10.1080/13814788.2017.1375092

Korstjens, I., & Moser, A., (2017). Series: Practical guidance to qualitative research. Part 2: Context, research questions and designs. *European Journal of General Practice* 23 (1): 274–79. https://doi.org/10.1080/13814788.2017.1375090.

Krieb, D. (2018). Assessing the impact of reference assistance and library instruction on retention and grades using student tracking technology. *Evidence Based Library and Information Practice* 13(2): 2–12. https://doi.org/10.18438/eblip29402.

Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management*, *34*(3), 387–394. https://doi.org/10.1016/j.ijinfomgt.2014.02.002

Lacerenza, Christina N., Shannon L. Marlow, Scott I. Tannenbaum, and Eduardo Salas. (2018). Team development interventions: Evidence-based approaches for improving teamwork. *AMERICAN PSYCHOLOGIST* 73 (4), 517–31. https://doi.org/10.1037/amp0000295.

Lee, G. (2021). Clarifying the complexities of qualitative research: A book review of phillip adu's A step-by-step guide to qualitative data coding. *The Qualitative Report*, *26*(7), 2168-2170. doi:http://dx.doi.org/10.46743/2160-3715/2021.4947

Levitt, H. M., Motulsky, S. L., Wertz, F. J., Morrow, S. L., & Ponterotto, J. G. (2017). Recommendations for designing and reviewing qualitative research in psychology: Promoting methodological integrity. *Qualitative Psychology*, *4*(1), 2–22. https://doi.org/10.1037/qup0000082

Lichtman, M. (2017). Judging the research process and product. *Qualitative research for the social sciences*. SAGE Publications. https://www-doi-org.ezp.waldenulibrary.org/10.4135/9781544

Lomet, D. B. (2017). The Future of Data Management. *Computer*, *50*(10), 12–13. https://doi.org/10.1109/MC.2017.3641630

Lourens, A., & Bleazard, D. (2016). Applying Predictive Analytics in Identifying Students at Risk: A Case Study. *South African Journal of Higher Education*, *30*(2), 129–142. https://eds-b-ebscohost-com.ezp.waldenulibrary.org/eds/pdfviewer/pdfviewer?vid=1&sid=c9db1d31-f1b8-43b0-8c03-9056517fe02b%40pdc-v-sessmgr01

Madill, A., & Sullivan, P. (2018). Mirrors, portraits, and member checking: Managing difficult moments of knowledge exchange in the social sciences. *Qualitative Psychology* (5) 3: 321–39. https://doi.org/10.1037/qup0000089.

Magaldi, D., & Berler, M. (2018). Semi-Structured interviews. *Encyclopedia of Personality and Individual Differences*, edited by Virgil Zeigler-Hill and Todd K.

Shackelford. (Chaps 1-6). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-28099-8_857-1.

Mah, D. (2016). Learning analytics and digital badges: Potential impact on student retention in higher education. *Technology, Knowledge and Learning, 21*(3), 285-305. doi:http://dx.doi.org.ezp.waldenulibrary.org/10.1007/s10758-016-9286-8

Maher, C., Hadfield, M., Hutchings, M., & de Eyto, A. (2018). Ensuring Rigor in Qualitative Data Analysis: A Design Research Approach to Coding Combining NVivo With Traditional Material Methods. *International Journal of Qualitative Methods*, *17*(1), 1–13. https://doi-org.ezp.waldenulibrary.org/10.1177/1609406918786362

Mahroeian, H., Daniel, B., & Butson, R. (2017). The perceptions of the meaning and value of analytics in New Zealand higher education institutions. *International Journal of Educational Technology in Higher Education* 14(1): 1–17. https://doi.org/10.1186/s41239-017-0073-y.

Manyanga, F., Sithole, A., & Hanson, S. (2017). Comparison of student retention models in undergraduate education from the past eight decades. *Journal of Applied Learning in Higher Education* 7, 30–42. EJ1188373.pdf (ed.gov)

Matsebula, F., and E. Mnkandla. (2017). A big data architecture for learning analytics in higher education. *IEEE AFRICON*: 951–56. https://doi.org/10.1109/AFRCON.2017.8095610.

Maxwell, J. (2008). Designing a qualitative study. *Qualitative Research*. https://doi.org/10.4135/9781483348858.n7.

Meadows KA. (2003). So you want to do research? 3. An introduction to qualitative methods. *British Journal of Community Nursing*, *8*(10), 464–469. https://www.researchgate.net/publication/9037262_So_you_want_to_do_research_3_An_introduction_to_qualitative_methods

Merriam, S. B. (2015). *Qualitative Research: A Guide to Design and Implementation, 4th Edition* (4 edition). John Wiley & Sons.

Merriam, S. B., & Tisdell, E. J. (2016). *Qualitative Research: A Guide to Design and Implementation*. John Wiley & Sons.

Mills, A., Durepos, G., & Wiebe, E. (2010). *Encyclopedia of Case Study Research*. SAGE Publications. https://doi.org/10.4135/9781412957397.

Murray, A. (2015). Academic libraries and high-impact practices for student retention: Library deans' perspectives. *Portal: Libraries and the Academy* 15 (3), 471–87. https://doi.org/10.1353/pla.2015.0027.

Nadasen, D., & List, A. (2017). Predicting four-year student success from two-year student data. *Big Data and Learning Analytics in Higher Education: Current Theory and Practice*, edited by Ben Kei Daniel. 221–36. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-06520-5_13.

Nathan, S., Newman, C., & Lancaster, K. (2018). Qualitative interviewing. *Handbook of Research Methods in Health Social Sciences*, edited by Pranee Liamputtong, 1–20. https://doi.org/10.1007/978-981-10-2779-6_77-1.

National Center for Education Statistics. (2020). *Undergraduate retention and graduation rates.*

https://nces.ed.gov/programs/coe/indicator_ctr.asp#:~:text=Retention%20rates%20measure%20the%20percentage,a%20specified%20period%20of%20time

Neelakantan, S. (2019). *'Data Analytics Can Save Higher Education', Say Top College Bodies*. Technology Solutions That Drive Education. Retrieved April 13, 2020, from https://edtechmagazine.com/higher/article/2019/11/data-analytics-can-save-higher-education-say-top-college-bodies

Niebel, T., Rasel, F., & Viete, S. (2019). BIG data – BIG gains? Understanding the link between big data analytics and innovation. *Economics of Innovation and New Technology*, *28*(3), 296–316. https://doi.org/10.1080/10438599.2018.1493075

Nimmagadda, S. L., & Rudra, A. (2017). Managing the Embedded Digital Ecosystems (EDE) Using Big Data Paradigm. In B. Kei Daniel (Ed.), *Big Data and Learning Analytics in Higher Education: Current Theory and Practice* (pp. 43–72). Springer International Publishing. https://doi.org/10.1007/978-3-319-06520-5_5

Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic analysis: Striving to meet the trustworthiness criteria. *International Journal of Qualitative Methods*. https://doi.org/10.1177/1609406917733847

O'Kane, P., Smith, A., Lerman, M.P. (2021). Building transparency and trustworthiness in inductive research through computer-aided qualitative data analysis software. *Organizational Research Methods*, *24*(1), 104–139. https://doi.org/10.1177/1094428119865016

Olaya, D., Vásquez, J., Maldonado, S., Miranda, J., & Verbeke, W. (2020). Uplift - 1modeling for preventing student dropout in higher education. *Decision Support*

Systems. 134. https://doi.org/10.1016/j.dss.2020.113320.

Patton, M. (2015). *Qualitative Research & Evaluation Methods.* SAGE. https://us.sagepub.com/en-us/nam/qualitative-research-evaluation-methods/book232962.

Perrotta, K. (2020). Getting HIP: A study on the implementation of asynchronous discussion boards as a high-impact practice in online udergraduate survey history courses. *The Journal of Social Studies Research* 44 (2), 209–17. https://doi.org/10.1016/j.jssr.2020.02.001.

Premalatha, K. (2019). Course and program outcomes assessment methods in outcome-based education: A review. *Journal of Education* 199 (3), 111–27. https://doi.org/10.1177/0022057419854351.

Priniski, S. J., Hecht, C. A., & Harackiewicz, J. M. (2018). Making Learning Personally Meaningful: A New Framework for Relevance Research. *Journal of Experimental Education*, *86*(1), 11–29. https://www.researchgate.net/publication/320478264_Making_Learning_Personally_Meaningful_A_New_Framework_for_Relevance_Research

Provencher, A. & Kassel, R. (2019). High-impact practices and sophomore retention: Examining the effects of selection bias. *Journal of College Student Retention: Research, Theory & Practice* 21 (2), 221–41. https://doi.org/10.1177/1521025117697728.

Roberts, L., Chang, V., & Gibson, D. (2016). Ethical considerations in adopting a university and system wide approach to data and learning analytics. *Big Data and*

Learning Analytics in Higher Education: Current Theory and Practice, edited by Ben Kei Daniel, 89–108. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-06520-5_7.

Romero, C., Ventura, S. (2007). Educational data mining: A survey from 1995 to 2005. Expert Systems with Applications, 33, 135–146. https://www.researchgate.net/publication/222815211_Educational_data_mining_A_survey_from_1995_to_2005

Rubel, A., & Jones, K. (2017). Data Analytics in Higher Education: Key Concerns and Open Questions. *University of St. Thomas Journal of Law and Public Policy (Minnesota)*, *11*, 25. Rubel Jones Big Data in Higher Education (ssrn.com)

Sass, D. A., Castro-Villarreal, F., Wilkerson, S., Guerra, N., & Sullivan, J. (2018). A Structural Model for Predicting Student Retention. *The Review of Higher Education*, *42*(1), 103–135. https://doi.org/10.1353/rhe.2018.0035

Sanders, L. D., Daly, A.P., & Fitzgerald, K. (2016). Predicting retention, understanding attrition: A prospective study of foundation year students. *Widening Participation & Lifelong Learning* 18 (2), 50–83. https://doi.org/10.5456/WPLL.18.2.50.

Saunders, B., Sim, J., Kingstone, T., Baker, S., Waterfield, J., Bartlam, B., Burroughs, H., & Jinks. C. (2017). Saturation in qualitative research: Exploring its conceptualization and operationalization. *Quality & Quantity* 52(4): 1893–1907. https://doi.org/10.1007/s11135-017-0574-8.

Schneider, M., & Preckel, F. (2017). Variables associated with achievement in higher education: A systematic review of meta-analyses. *Psychological Bulletin,* 143(6):

565–600. doi: 10.1037/bul0000098.

Seaman, M. (2011). Bloom’s taxonomy: Its evolution, revision, and use in the field of education. *Curriculum and Teaching Dialogue*. 1–2(29).

Shanahan, J. G., & Dai, L. (2015). Large scale distributed data science using apache spark. *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2323–2324. https://www.researchgate.net/publication/297582750_Large_Scale_Distributed_Data_Science_using_Apache_Spark

Shein, E. (2020). How universities deploy student data. *Communications of the ACM*. *Association for Computing Machinery*. doi:10.1145/3381910

Shufutinsky, A. (2020). Employing use of self for transparency, rigor, trustworthiness, and credibility in qualitative organizational research methods. *Organizational Development Review* 52 (1), 50-58. *https://www.researchgate.net/publication/340539936_Employing_Use_of_Self_for_Transparency_Rigor_Trustworthiness_and_Credibility_in_Qualitative_Organizational_Research_Methods*

Silverman, D. (2016). *Qualitative Research*. SAGE.

Singh, D., & Reddy, C. K. (2015). A survey on platforms for big data analytics. *Journal of Big Data*, *2*(1) 8. A survey on platforms for big data analytics | Journal of Big Data | Full Text (springeropen.com)

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of big data challenges and analytical methods. *Journal of Business Research* 70 (1), 263–86. https://doi.org/10.1016/j.jbusres.2016.08.001.

Slater, S., Srećko J., Vitomir K., Ryan S. B,, and Dragan G. (2017). Tools for educational data mining: A review. *Journal of Educational and Behavioral Statistics* 42 (1) 85–106. https://doi.org/10.3102/1076998616666808.

Soares, L., Steele, P., & Wayt, L. (2016). Evolving higher education business models. *American Council on Education: Center for Policy Research and Strategy*. *https://www.acenet.edu/Documents/Evolving-Higher-Education-Business-Models.pdf*

Spiers, J., Morse, J.M., Olson, K., Mayan, M., & Barrett, M. (2018). Reflection/Commentary on a past article: Verification strategies for establishing reliability and validity in qualitative research. *International Journal of Qualitative Methods* 17(1). https://doi.org/10.1177/1609406918788237.

Stage, F. K., & Hossler, D. (2000). Where is the student? Linking student behaviors, college choice and college persistence. In J. M. Braxton (Ed.), *Reworking the departure puzzle* (pp. 170–195) Nashville, TN: Vanderbilt University Press. https://www.researchgate.net/publication/282861589_Where_Is_the_Student_Linking_Student_Behaviors_College_Choice_and_College_Persistence

Stahl, N., & King, J. R. (2020). Expanding approaches for research: Understanding and using trustworthiness in qualitative research. *Journal of Developmental Education* 44 (1): 26–28. https://www.researchgate.net/publication/337224462_Expanding_Approaches_for_Research_Action_Research

Stefanova, K. & Kabakchieva, D. (2017). Educational data mining perspectives within university big data environment. International Conference on Engineering, Technology and Innovation (ICE/ITMC), Funchal, 2017, pp. 264-270, doi: 10.1109/ICE.2017.8279898.

Swafford, S. J. (2017). Factors affecting retention of first-time, full-time freshmen students at higher education institutions within the Appalachian college association. University of Tennessee at Chattanooga, Tennessee. https://www.researchgate.net/publication/346425936_Expanding_Approaches_for_Research_Understanding_and_Using_Trustworthiness_in_Qualitative_Research

Terrón, M., Olivencia, J. J. L., & Caballero, P. D. F. (2010). Big data irruption in education." *Irrupción Del Big Data En La Educación.*, 57(3) 59–90. https://doi.org/10.12795/pixelbit.2020.i57.02.

Tierney, W. G. (2016). An Anthropological Analysis of Student Participation in College. *The Journal of Higher Education*, *63*(6), 603–618. https://doi.org/10.1080/00221546.1992.11778391

Tight, M. (2020). Student retention and engagement in higher education. *Journal of Further and Higher Education* 44 (5), 689–704. https://doi.org/10.1080/0309877X.2019.1576860.

Tinto, V. (2006). Research and practice of student retention: What next? *Journal of College Student Retention: Research, Theory & Practice* 8 (1), 1–19. https://doi.org/10.2190/4YNU-4TMB-22DJ-AN4W.

Tobin, G. A., Begley, C. M. (2004). Methodological rigour within a qualitative framework. Journal of Advanced Nursing, 48, 388–396. doi:10.1111/j.1365-2648.2004.03207.x

Torrecilla, J. L., & Romo, J. (2018). Data learning from big data. *Statistics & Probability Letters*: *The role of Statistics in the era of big data*. 136: 15–19. https://doi.org/10.1016/j.spl.2018.02.038.

Tsai, C.-W., Lai, C.-F., Chao, H.-C., & Vasilakos, A. V. (2015). Big data analytics: A survey. *Journal of Big Data*, *2*(1), 21. Big data analytics: a survey | Journal of Big Data | Full Text (springeropen.com)

Tukey, J. W. (1977). *Exploratory data analysis.* Reading, MA: Addison-Wesley

Wang, Y. (2017). Education policy research in the big data era: Methodological frontiers, misconceptions, and challenges. Education Policy Analysis Archives, 25(94). http://dx.doi.org/10.14507/epaa.25.3037

Wayt, L. & La Cost, B. (2016). Transitioning to performance-based state funding: Concerns, commitment, and cautious optimism. *Faculty Publications in Educational Administration*. https://digitalcommons.unl.edu/cehsedadfacpub/112.

Welsh, E. (2002). Dealing with data: Using NVivo in the qualitative data analysis process. Forum, Qualitative Social Research, 3. http://www.qualitativeresearch.net/fqs/fqs-eng.htm

White, D. E., Oelke, N. D., Friesen, S. (2012). Management of a large qualitative data set: Establishing trustworthiness of the data. International Journal of Qualitative Methods, 11, 244–258. doi:10.1177/160940691201100305

Whitford, E. (2020). Colleges walk back fall reopening plans and opt for online-only instruction. https://www.insidehighered.com/news/2020/08/12/colleges-walk-back-fall-reopening-plans-and-opt-online-only-instruction

Wilderotter, R. (2020, July 22). How higher ed can use predictive analytics for student recruitment and retention. *BPLogix. https://www.bplogix.com/blog/predictive-analytics-student-retention*

Williamson, B. (2017). Who owns educational theory? Big data, algorithms and the expert power of education data science. *E-Learning and Digital Media* 14 (3)105–22. https://doi.org/10.1177/2042753017731238.

Xerri, M. J., Radford, K., & Shacklock, K. (2018). Student engagement in academic activities: A social support perspective. *Higher Education* 75 (4), 589–605. https://doi.org/10.1007/s10734-017-0162-9

Appendix A: Interview Protocol

Participant ______________________________
____

Hi _______, thank you for volunteering to participate in my research study with this interview. Have you reviewed and signed the informed consent form? It gives guidelines for us both about the purpose of the interview and the rights you have as a participant. To remind you, I will be recording the interview to help me capture your thoughts. With your permission, may I start the recording? Great, thank you. START BOTH RECORDERS

We've already confirmed that you meet the participant requirements. As you know, I'm interviewing administrators of 4 year, U.S., colleges that have a job title or responsibilities for data mining in retention initiatives at their institution. So, what I'm trying to better understand the perceptions and experiences of administrators in these roles. It is my hope that you will be very candid when you describe your thoughts and perceptions. There's no judgment on my part, I just want to understand what processes are in place for identifying and applying student data to retention initiatives, specifically for tracking and predicting.

As the researcher, I'm supposed to be very much a listener and not a talker. So, as I ask questions, if it seems like I am a little removed, that's because I am; I'm supposed to be. But be sure, I AM listening and very much interested in your ideas and will be taking notes so I do not miss anything when playing back this recording.

I will start with a few questions that help understand more about you.

1. What is your exact title and how long have you been in this position at your current institution? ____
2. What are your specific responsibilities in retention initiatives in your current position? _____________
3. Is your institution private or public and profit or non-profit? (Circle answers)

The following Questions will specifically align to the RQ of this study

Conceptual Framework	Focus of the RQ	Interview Question
Gandomi & Haider Three V Model and Attarran et al., Three Pronged Approach Model – basic data mining language	Tracking and Predicting Retention	Tell me about your responsibilities for student retention data at your institution and whether these are under your job description title or assigned to you as responsibilities from your supervisor.
Gandomi & Haider Three V Model – use of volume, velocity, and variety; and Attarran et al., Three Pronged Approach Model – Use of Prescriptive, Predictive, and descriptive data	Perceptions and experiences of higher education administrators of 4-year colleges in the application of student data	What are your perceptions and experiences of the data mining processes for retention in all student levels at your institution? EX: Undergrad? Just Grad? Just Online? Please indicate if your perceptions are from experiences or fringe conversations.
Gandomi & Haider Three V Model and Attarran et al., Three-Pronged Approach Model – basic data mining language	Experiences of higher education administrators of 4-year colleges in the application of student data……retention	Tell me your experiences with the process for identifying student attributes for use as variables in retention initiatives.
Gandomi & Haider Three V Model and Attarran et al., Three Pronged Approach Model – basic data mining language	Perceptions and experiences of higher education administrators of 4-year colleges….tracking and predicting retention	Please explain further why this data mining format was chosen for data reporting? What insight can you give if this same format is used in tracking and predicting retention?
Gandomi & Haider Three V Model – use of volume, velocity, and variety; and Attarran et al., Three Pronged Approach Model – Use of Prescriptive, Predictive, and descriptive data	Perceptions and experiences of higher education administrators of 4-year colleges in the application of student data	What student data have you identified through the data mining process as significant for tracking and predicting retention?

Gandomi & Haider Three V Model – use of volume, velocity, and variety; and Attarran et al., Three Pronged Approach Model – Use of Prescriptive, Predictive, and descriptive data	Applies to all elements of the RQ	What is your perception of the sufficiency of these variables based on the needs of your institution to track and predict student retention?

RQ 1: What are the perceptions and experiences of higher education administrators of 4-year colleges in the application of student data targeted for tracking and predicting retention?

Probes (all may or may not be used)

a. Please tell me about how these variables are sufficient or not sufficient for the needs of your institution to track and predict student retention?
b. How do you perceive your culture in terms of data informed decision making?
c. What insight can you share from either your perceptions or experiences related to assets and barriers to success in identifying and apply student data to tracking and predicting retention?

Concluding Statement to Participant:

Thank you so much for participating in this interview. You have been generous with your time and answers and this has provided insight for me. Later, I will be in contact via email to share the study's initial findings. You will also have access to the completed report, if you would like. If you have any questions about the process or results, you may reach out to me by email or phone.

Do you have any additional questions for me?

Thanks for your time; I'll be in touch soon!

STOP BOTH RECORDERS

Contact Summary Form

RQ - Perceptions	
RQ – Experiences	
Institutional Hindrances	
Institutional Positives	

Name: ____ Date: ______________________

1. **What were the main topics or concepts you found interesting or profound in this interview?**

2. **Anything remaining that you believe is pressing to mention and add to your statements?**

Appendix B: Consent Language for Email Recruitment Message

You are invited to take part in a research study that will investigate the perceptions and experiences of administrators of 4 year U.S. colleges of how they apply student data to predicting and tracking retention. You were randomly chosen for the study because you are an academic leader at your institution with the position title or have responsibilities for data mining in retention initiatives. Please read this email and ask any questions you have before agreeing to be part of the study. Your reply and acceptance via email determines your informed consent and willingness to volunteer your time for this study.

This study is being conducted by Judee Mulhollen, who is a doctoral student at Walden University in the Higher Education Leadership and Management program.

Background Information:

The purpose of this basic qualitative study is to explore the perceptions and experiences of administrators of 4-year colleges in their application of student data for tracking and predicting retention.

Procedures:

Materials related to your participation will be the audio recorded interviews and transcription of interview notes by me, the researcher.

If you agree to be in this study, you will be asked to:

Participate in a one-on-one recorded interview via phone or Zoom, virtual format. The interview will last approximately 60 minutes.

After the content of your interview has been transcribed, you will be asked to review the content and may request changes if needed. This will be done via email, and you will be asked to respond within one week. Please allow approximately 30 minutes for this review.

Once initial interpretation of your interview has been completed, you will be contacted a second time and asked to verify that your intentions are represented accurately. This will be done via email, and you will be asked to respond within one week. Again, please allow up to 30 minutes for this review.

Voluntary Nature of the Study:

Your participation in this study is voluntary. This means that your decision is respected whether or not you want to be in the study. If you decide to join the study now, you can still change your mind later. If you feel stressed during the study, you may stop at any time. You may skip any interview questions that you feel are uncomfortable.

Risks and Benefits of Being in the Study:

This study may clarify academic leadership perceptions of BDA and its applications in higher education as well as the supports and barriers to the professional development and training in BDA and its functions to higher education. The participant discussion of supports and barriers to BDA training and professional development can be a cause of concern for those uncomfortable discussing both the positives and negatives of particular institutional work culture.

Compensation:

There will be no compensation awarded for participation in this study.

Confidentiality:

Any information you provide will be kept confidential. The researcher will not use your information for any purposes outside of this research study. Also, the researcher will not include your name or anything else that could identify you in any reports of the study.

Contacts and Questions:

The researcher’s name is Judee Mulhollen. The researcher’s faculty advisor is Steven Wells. You may ask any questions at any time at the beginning, middle, or end of this study. You may contact the researcher via email at judee.mulhollen@waldenu.edu or the advisor at steven.wells@mail.waldenu.edu. If you would like to speak to someone in the Research Center at Walden University regarding your rights and responsibilities, you may contact the Research Participant Advocate 800-925-3368, extension 1210.

Statement of Consent:

I have read the above information. I have received answers to any questions and have the contact information for future questions. I am 18 years of age or older, and I consent to participate in the study. But typing my name below and replying to this email consent form, this serves as approval for volunteering as a participant in this study.

Printed Name of Participant Below Date

Appendix C: A priori Codes from Conceptual Frameworks of This Study

- Volume – as defined by Gandomi and Haider (2015)
- Velocity – as defined by Gandomi and Haider (2015)
- Variety – as defined by Gandomi and Haider (2015)
- Predictive analytics – as defined by Attaran, et al (2018)
- Prescriptive Analytics - as defined by Attaran, et al (2018)
- Descriptive Analytics - as defined by Attaran, et al (2018)