ABSTRACT

A Complex Perspective on Student Success Programming:
A Quantitative Analysis of Retention Rates for Sophomores Who Experience Differentiated Coaching While Attending a Guided Pathways Community College

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Despite efforts to place students on a guided pathway to successful completion, nearly one in five students who do not persist at community colleges complete 75% or more of the credit threshold for a degree before leaving the institution (Johnstone, 2018). In Texas, according to the Texas Higher Education Coordinating Board Members (THECB, 2020), 28% of community college students graduate with an associate degree, bachelor's degree, or certificate within three years. At Chaparral Community College, the percentage is even less, at 24% (THECB, 2020). This evidence points to a need for retention reform, focusing on sophomore students.

This quantitative study used two pillars of the Guided Pathways model, helping students stay on the path and ensuring students are learning, as a framework for analysis. The study employed a complex approach to broaden the definition of academic integration (Tinto, 1993) by including experiences beyond the classroom resulting from enrollment in courses (Latz, 2015). By taking a complex perspective, the study used differentiated coaching as an approach to accomplish academic integration in and out of the classroom. Two logistic regression models were used to examine the differentiated coaching approach deployed through student success programming as a predictor of retention ($N = 1050$), semester one to semester two and semester one to semester three.

Initiatives aimed at retention that involve cross-institutional reform are challenging to evaluate and often take years to observe improvements (Bailey et al., 2015). This study demonstrated this struggle as the treatment, although positively sloped, did not have a statistically significant relationship to retention in the transition from the first semester to the second. However, when students moved along their pathway to the third semester, the differentiated coaching treatment had a positive and significant relationship to retention. Therefore, there was an increased probability of being retained for students who received differentiated coaching. This upward trend is expected to continue as the advisors develop their expertise in differentiated coaching and the application to students' individual experiences.

Keywords: community college, retention, attrition, sophomore, guided pathways, differentiated, student success, advising

A Complex Perspective on Student Success Programming: A Quantitative Analysis of Retention Rates for Sophomores Who Experience Differentiated Coaching While Attending a Guided Pathways Community College

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> Walk with the dreamers, the believers, the courageous, the cheerful, the planners, the doers, the successful people with their head in the clouds and their feet on the ground. Let their spirit ignite a fire within you to leave this world better than when you found it.
>
> –Wilferd Peterson

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DEDICATION

To my daughter

Presley Rein

You can do hard things.

"Be on your guard; stand firm in the faith; be courageous; be strong."

1 Corinthians 16:13

CHAPTER ONE

Background and Needs Assessment

Introduction

Despite efforts to place students on a guided pathway to successful completion, nearly one in five students who do not persist at community colleges complete 75% or more of the credit threshold for a degree before leaving the institution (Johnstone, 2018). This evidence points to a need for retention reform, focusing on sophomore students. This finding is contrary to many retention reforms that historically have been aimed at incoming freshmen students. The phenomenon of student attrition negatively impacts the student and the institution.

To address low completion rates and stagnant retention rates, many community colleges now implement an initiative called Guided Pathways (Bailey et al., 2015; Jenkins, Brown, et al., 2018). College administrators designed Guided Pathways to help students stay on track to completing their educational goal of obtaining an associate degree, certificate of completion, or successful transfer to a four-year institution. Guided Pathways often include a student's major, or area of study, corresponding degree plan, and various programming or methods intended to communicate the pathway (Jenkins, Brown, et al., 2018).

For Guided Pathways to have a significant enough impact to positively influence student retention and subsequently student completion, this research study demonstrated that a complex approach was needed to view the initiative holistically and not siloed by department, program, or student group (Bailey et al., 2015). This study concentrated on a specific segment of Guided Pathways by taking a complex perspective on student success programming. The purpose of this quantitative study was to test a Guided Pathways framework to determine the relationship between differentiated coaching, as deployed in student success programming through the Guided Pathways initiative, and retention for associate degree-seeking or general transfer students who have completed at least thirty hours at Chaparral Community College.

Statement of the Problem

Approximately 30% of community college students across the United States earn their associate degrees within three years (Johnstone, 2018). In Texas, according to the Texas Higher Education Coordinating Board Members (THECB, 2020), 28% of community college students graduate with an associate degree, bachelor's degree, or certificate within three years. At Chaparral Community College, the percentage is even less, at 24% (THECB, 2020). These statistics demonstrate a need across colleges regardless of student demographics.

The state of Texas established benchmarks indicating the percentage of students who must complete a certificate, associate, bachelor's, or master's degree within a designated time period (THECB, 2015). In conjunction with the American Community College Association, the Texas Success Center promoted the Guided Pathways model to accomplish these benchmarks (TACC, 2021). The flexibility in the model allowed each institution to define Guided Pathways to meet its student population's unique needs. Guided Pathways outlined educational program maps, including specific "course sequences, progress milestones, and program learning outcomes" that align to expectations of students upon program completion (Jenkins, Lahr, et al., 2018, p. 1).

The part of the Guided Pathways model that seems to be lacking in retention research and best practices is “helping students stay on their path.” At a community college, this refers to students who have completed at least 30 credit hours. Research shows that many students who have completed 30 or more credit hours stop or drop out (Johnstone, 2018). Many community colleges focus on students and their first-semester experience (Pascarella & Terenzini, 1980; Reader, 2018; Schaeper, 2020; Schroeder, 2013). Institutions pay little attention to those students “in the middle” or what would be considered the sophomore level. Although little evidence exists at the community college level, a few studies have been completed at the university level regarding this group in the middle (Gump, 2007; Tower et al., 2015; Webb & Cotton, 2019). Using a quantitative study, Webb and Cotton (2019) sought to decipher the “sophomore slump” by examining student perceptions after the first year. The study noted positive results for social integration and perceptions of teachers (Webb & Cotton, 2019). However, when rating perceptions of courses being enjoyable and meeting expectations, there was a decrease in positivity (Webb & Cotton, 2019). The results coupled perceptions with a reported increase in thoughts about dropping out (Webb & Cotton, 2019). I noted several possible reasons for the findings but had no concrete evidence to support the claims (Webb & Cotton, 2019).

Despite limited research in this area, studies exist that focus on specific services generally associated with Guided Pathways. One quantitative analysis examined the relationship between advising outreach and student retention, academic progress, and achievement (Schwebel et al., 2012). Schwebel et al. (2012) concluded, upon analyzing the longitudinal data of 501 students, that although the number of advising appointments increased, there was no association to retention, academic progress, and achievement at a significant level. Other studies delved into theories such as adaptability (Martin et al., 2013), self-efficacy (Gore, 2006), student commitment and perceptions of institutional commitment (Savage et al., 2019), and alternate advising models (Zhang et al., 2019) as predictors of student success. These findings reinforced the idea that multiple interventions along a guided academic pathway are necessary to promote student success. However, there remains a need to explore how students engage in these interventions as part of Guided Pathways.

Prior to the development of formal Guided Pathways at Chaparral Community College, academic advising, academic coaching, wellness support, and academic probation comprised the student success programming. The approach was primarily transactional, focused more on process than student need. Each program works independently of the other, meaning there was traditionally little to no crossover of initiatives. While each program has experienced successes, there is opportunity for improvement to impact overall student retention or completion rates. The need for research on intentionally designed retention reform focused on sophomore level students at a community college is imperative.

Literature Review

Students who attend community colleges need support to help them be successful and complete their academic journey. Increasing student retention rates presents a complex problem for community colleges. The following literature review first outlines complexity theory to explain in what ways student retention is a complex problem (Davis et al., 2012; Davis & Simmt, 2016; Holland, 2014; Mitchell, 2009). Several key ideas from complexity theory relate two Guided Pathways' pillars, namely, help students stay on their path and ensure students are learning (American Association of Community Colleges, 2021; Jenkins, Lahr, et al., 2018).

Next, the definition of academic integration (Tinto, 1993) does not have to be merely confined to the classroom; it can more broadly include academic experiences that occur both in and out of the classroom (Latz, 2015; Tinto, 1993). The complex perspective of using "inclusive-or" logic (Aoki, 2004; Pratt, 2008a) applied to the inclusion of academic experiences outside of the classroom generates extended support for students to stay on their path and ensure students are learning. Then I explore best practices found in student success programming that occur beyond the bounds of the classroom (e.g., advising, academic probation, wellness support, academic coaching). While these approaches each can offer support to students, research has exposed that alone each does not make a significant difference (Bailey et al., 2015; Gore, 2006; Martin et al., 2013; Savage et al., 2019; Schwebel et al., 2012; Zhang et al., 2019). A complex lens that integrates these as a network of relations emerges as a unique approach, termed differentiated coaching. Finally, complexity theory, academic integration, and differentiated coaching combine to form a conversation regarding student retention embedded within the Guided Pathways (American Association of Community Colleges, 2021; Jenkins, Lahr, et al., 2018) framework.

Complexity Theory

Researchers of complex systems agree on one thing: there is no one agreed upon definition as the theory is situational and can be applied to many different fields of study (Davis et al., 2012; Davis & Simmt, 2016; Holland, 2014; Mitchell, 2009). According to

Mitchell (2009), the term complex system means "a system in which large networks of components with no central control and simple rules of operation give rise to complex collective behavior, sophisticated information processing, and adaptation via learning or evolution" (p. 302). Mitchell (2009) likens this to the immune system that is made up of simple components. These components, or cells, do not have any central control and yet function together as a unit when faced with external threats. This type of adaptive behavior for the system most closely aligns with this study. Complex systems that adapt to interactions with other entities to improve chances of success through a learning process are referred to by researchers as complex adaptive systems (Davis et al., 2012; Davis & Simmt, 2016; Holland, 2014; Mitchell, 2009).

Academic institutions can be analyzed as complex systems, each one unique based on the interactions of the components within the system. At first glance, two-year higher education institutions appear to have similar programming aimed to assist students in staying on their path to completion. They each have a department of student services with programs, such as advising, academic probation, and college readiness. However, upon closer analysis, this programming can vary drastically from institution to institution. Davis et al. (2012) included this in their research noting "the rules that govern complex systems can vary dramatically from one system to the next—even when the systems appear to be virtually identical" (p. 375). The variance is because student success programming can be multifaceted, and students bring unique challenges. Although there are best practices and plans to assist students, outcomes cannot be predicted; the path is not linear (Davis & Simmt, 2016; Pratt, 2018). By treating success programming grounded in differentiated coaching as a complex adaptive system, adaptation occurs as components shift and change to better align with the needs of the students (Davis et al., 2012). Next, I explore the theories of retention to determine the relationship between success programming grounded in differentiated coaching and the success of students.

Retention

A short-term measure of academic success that leads to completion is student retention (Aljohani, 2016; Latz, 2015; Tinto, 1993). As used in this study, retention refers to the percentage of students who return to the same institution the following semester (Texas Higher Education Coordinating Board Members, 2021b). The unfortunate reality for many institutions, both large and small, two-year and four-year, is that retention rates are often stagnant (Chaparral Community College, 2021). As a result, scholars have proposed many college reforms to improve retention rates (Bailey et al., 2015). College reforms are reviewed later in this section.

Several theories of attrition aim to explain the phenomenon of college students dropping or stopping out. Stopping out refers to students who leave college to return to either the same or another institution (Tinto, 1993). One of the most prevalent theories is Tinto's (1993) Theory of Institutional Departure. Researchers in the 1970's, including Tinto, moved beyond individual attributes as predictors of retention. These scholars considered the institution as well (Aljohani, 2016). Tinto (1993) recognized the impact of experiences within the institution through social and academic integration. His research primarily focused on traditionally aged students at four-year institutions; however, many of his model components can apply to traditional and non-traditional students enrolled at a two-year college.

Metz (2004) provided a historical review of persistence literature, and noted previous research omitted the two-year college. Researchers began applying retention theories to two-year colleges to note missing variables (Okun et al., 1996; Terenzini & Pascarella, 1994). Terenzini and Pascarella (1994) found that many community college students are nonresidential and do not spend the same amount of time on campus as traditional residential students. Therefore, social integration (Tinto, 1993) was either minimal or absent. Okun et al. (1996) studied part-time students, a typical student demographic in community colleges. They found connections among the number of credit hours enrolled in each term, grade point average, and persistence (Okun et al., 1996). Researchers had not previously applied such student characteristics to retention models (Metz, 2004).

The academic integration portion of the model explained how students build connections with their institution through attending courses (Tinto, 1993). A more recent study by Latz (2015) further defined academic interactions as occurring in an academic setting instead of the classroom only. Latz (2015) referred to academic integration as being of higher importance than social integration in community colleges, especially those with commuter campuses. The Guided Pathways reform comprised initiatives and programming to foster varying types of academic interactions (Jenkins, Lahr, et al., 2018) by expanding the focus to include a complex perspective of an "inclusive-or" logic (Aoki, 2004; Pratt, 2008a) applied to experiences outside the classroom.

At the time of this study, Chaparral Community College, primarily a commuter institution, made academic integration the primary avenue for student relationships. Students participated in success programming as a requirement of their enrollment in courses at Chaparral Community College. The opportunity for interactions through this programming and the classroom created the potential for a complex adaptive system. The components were relatively fixed; however, each faculty and staff member needed to adapt to each student's individual needs to influence their learning and pathway alignment. Utilizing academic integration allowed for the facilitation of lifeworthy learning (Perkins, 2014). Students sought to connect their college learning experiences and the career field or fields they chose to pursue (Merriam & Bierema, 2014). Student success staff structured support programming to explore big understandings, big questions, and big know-hows (Perkins, 2014). Success staff discussed these concepts outside the classroom in a manner specific to each student and their individual needs or understanding level.

For example, a student who is majoring in health information management might not understand why composition class is essential to their career and, as a result, is struggling in the class. During an academic coaching session, the student success specialist can discuss specific job-related tasks that reinforce the importance of correct grammar. In a hospital setting, written communication could be the difference between life or death. There is also an opportunity to explain the additional skills the student is learning that will be useful later in life; the big know-how (Perkins, 2014). In this example, the academic coaching session resulted from the student's enrollment in the composition class, thus providing an academic interaction outside the classroom. These types of interactions strengthen "fit," or the connection students have to their educational experience and the institution itself (Latz, 2015). A more in-depth review of the Guided Pathways initiative further explains this concept.

Guided Pathways

Although retaining students from one semester to the next endures as a goal of higher education institutions, educational leaders recently placed more emphasis on the completion of college degrees. The *Student Right to Know and the Campus Security Act* of 1990, which required the public disclosure of performance measures, sparred this shift in higher education reform (Bailey et al., 2015). For community colleges, the shift focused on educational outcomes, access, and success, instead of simply access (Bailey et al., 2015). As a result, education reforms emerged, funded by foundations such as the Lumina Foundation and the Bill and Melinda Gates Foundation (Bailey et al., 2015). Although well-intentioned, these reforms did not have the overall effect desired on improving outcomes due to the focused nature of the initiatives and the inability to institutionalize best practices. Success was occurring but not on a large enough scale to significantly impact graduation rates.

To address the dismal and often stagnant completion rates experienced by community colleges, educational leaders developed a Guided Pathways approach (Bailey et al., 2015; Completion by Design, 2016). This approach differed from previous initiatives as it involved whole college reform. It shifted from a focus on access to completing educational goals (Jenkins, Lahr, et al., 2018). Guided Pathways required consideration of programming, services, and instruction across the institution leading to rethinking the design from entry to completion (Bailey et al., 2015; Completion by Design, 2016). Educational reform entities identified and defined four pillars to guide institutions in this redesign process: “Mapping pathways to student end goals, helping students choose and enter a program pathway, keeping students on the path, and ensuring students are learning” (Jenkins, Lahr, et al., 2018, p. 3). These four pillars defined the framework for implementing the model, serving as intertwined concepts that can be deployed by each institution differently.

The first pillar of mapping pathways involves identifying the areas of study or broad category focused on certain career types that students may choose (American Association of Community Colleges, 2021; Completion by Design, 2016; Jenkins & Cho, 2014; Jenkins, Lahr, et al., 2018), often referred to as meta-majors in higher education. Once identified, faculty and staff map each program offered to the corresponding meta-major. A precise course sequence is made available to students within each program for a clear plan for completion. Pathways identify and explain courses critical to program success or transfer to a four-year institution. Further mapping includes creating embedded degree pathways to promote certificates and degrees collectively. This step lays the foundation for the student to select a career, determine the appropriate meta-major, and identify the degree and corresponding courses to reach their stated career goal.

Once an institution has committed to deploying Guided Pathways and faculty and staff map pathways, the process for which students select these pathways must be determined. Choosing and entering a program pathway may occur at multiple points depending on the onboarding processes and procedures in place. Career exploration should start at the beginning of the college experience as part of the onboarding process instead of the end when approaching completion. A mindset shift from semester-to-semester planning to full program planning is key to assisting students in understanding the requirements of the degree and the time it will take to complete (American Association of Community Colleges, 2021; Jenkins & Cho, 2014; Jenkins, Lahr, et al., 2018).

The Guided Pathways model intentionally redirects student support personnel to track student progress toward completion based on their designated program pathway. The redesign includes considering the student experience and the resources available to them to ensure they can see their progress at any point in time. Additionally, this pillar promotes rethinking how students receive advising (American Association of Community Colleges, 2021; Jenkins & Cho, 2014; Jenkins, Lahr, et al., 2018). An approach should be adopted that shifts practices from part-time versus full-time status to on-path versus off-path progress. Other examples include class scheduling to meet the student's needs and advisors monitoring course registration instead of students being expected to self-advise.

A final step in the implementation of this model is critically examining the relationship between the advisor's role and the instructor's role (American Association of Community Colleges, 2021; Completion by Design, 2016; Jenkins & Cho, 2014; Jenkins, Lahr, et al., 2018). Ensuring students are learning is a task consisting of mapping program learning outcomes to the community's employment needs in designated fields. Aligning outcomes to employment needs means rethinking assessment beyond a grade. The use of student portfolios to demonstrate and showcase a student's mastery of learning outcomes is encouraged. The faculty should utilize active and collaborative learning strategies to ascertain relevance to the student's future career choice. When possible, students should be allowed to explore internships, project-based learning, and service-learning to deepen those connections to the workplace (Jenkins, Lahr, et al., 2018).

Although success experts designed each of the four pillars to be used together to increase student retention and subsequently the attainment of educational goals, this study focuses on two: help students stay on their path and ensure students are learning. These two pillars align with academic integration as an essential step to finding a connection with the college community (Tinto, 1993).

In summary, within the Guided Pathways model, two pillars address academic integration that functions as a complex adaptive system. Thus, faculty and staff must consider a complex method to create the type of interactions needed. Success programming grounded in differentiated coaching considers the whole student when determining academic support. Differentiated coaching, as a complex method, responds to the identified Guided Pathways pillars.

Differentiated Coaching

To understand differentiated coaching, we must first understand the concept of differentiated instruction. The adjective "differentiated" derived from the field of differentiated instruction. Differentiated instruction is a student-centered teaching model that is proactive, is rooted in assessment, and is taking multiple approaches to content, process, and product (Tomlinson, 2017). The model provides the opportunity for learners with different cultural backgrounds, varied readiness levels, and sources of motivation, to thrive in the classroom by giving teachers flexibility (Tomlinson, 2017). According to Tomlinson (2017) teachers must assess where their students are to be able to adapt the learning environment to meet their needs. Scaffolding is an example of a differentiated instruction technique used to provide the support students need to meet their learning goals. Many of these techniques can be utilized by student success staff in support programming to meet the students' needs by facilitating learning. By applying the model of differentiated instruction to student success programming, advisors can focus on the student's needs first and then apply the appropriate intervention accordingly.

To demonstrate differentiated coaching is a unique approach through a complex lens that integrates each component as a network of relations, I created Figure 1.1 to display the interactions between where and how to engage in differentiated coaching. I refer to the bifurcation of these two main ideas as a complex perspective using an "inclusive-or" logic (Aoki, 2004; Pratt, 2008a) applied through differentiated coaching grounded in the two pillars of the Guided Pathway framework.

Figure 1.1. Differentiated coaching approach.

Note. The image of the Lorenz attractor was screen-grabbed from a gif image that maps a sample trajectory through phase space (Quinn, 2013).

First, I selected an image of the Lorenz attractor (Quinn, 2013). Lorenz (1995) developed a three-dimensional representation for chaotic flow in a dynamical system. This representation is a depiction of the pattern of an iterated function oscillating around two basins of attraction. In the case of differentiated coaching, the two basins are student success programming and theories and principles. Student success programming is where the intervention engagement occurs, and theories and principles detail how the engagement with the student occurs. The oscillation does not occur in a linear, deterministic pattern, but rather jumps back and forth between the two components. This division of two components can be described as a bifurcation, which is not a dichotomy of an either-or but shared possibilities of an inclusive-or (Pratt, 2008a).

Using the Lorenz attractor as a metaphor, I detailed interrelated facets within each basin of differentiated coaching (see Figure 1.1). For the basin of student success programming, the four locations are academic advising, academic coaching, probation programming, and wellness support. For the basin of theories and principles, the methods of holistic advising, motivational interviewing, and principles of adult learning are applied. Each facet can stand alone; however, when treated as separate entities, they cannot move a student toward academic integration at a desirable rate. Separately, these entities become siloed efforts with a narrow focus and limited reach. Differentiated coaching brings the seven together by keeping the student as the central focus.

Student success staff consider the needs of the students before determining the where or how to engage with individual students. Holistic advising encourages advisors to consider a student’s personal life aspects when planning for a future degree and career (Kardash, 2020). The foundational component of probation programming is education to help students understand the academic and financial implications (Higgins, 2003). Wellness support considers both internal and external factors that may affect a student's academic performance, including anxiety and depression (Harper & Peterson, 2005). Academic coaching involves a proactive intervention designed to assist students with classroom needs aside from content such as time management (McClellen & Moser, 2011). Student success staff utilize motivational interviewing to create rapport and build connections with students (Schiemann & Molnar, 2020). Lastly, the principles of adult learning are designed to facilitate the learning process (Knowles et al., 1998). To further understand the concept of differentiated coaching, I outline aspects fused with more traditional forms of success programming to highlight research supporting why advisors should incorporate them.

Holistic Advising

With the shift of community college focus to access and success (Bailey et al., 2015) came a new definition of holistic advising. Holistic advising is described as considering each student's personal attributes in addition to their academic merits and the influence each has on the ability to reach their educational goals (Kardash, 2020). Traditionally, holistic advising referred to a single component of an advising approach, not as a central design element (Kardash, 2020). The idea that simply opening the doors for students and expecting them to navigate their educational path on their own became a thing of the past (Drake, 2011). To promote student success, students need the opportunity to create human connections, build educational and career decision-making skills, and have access to support services, all of which holistic advising can be a catalyst

(Donaldson et al., 2016; Drake, 2011; Kalamkarian et al., 2017; Kardash, 2020; Lynch & Lungrin, 2018).

In general, community colleges do not have the staffing to sustain holistic advising models at the level of intent (Kalamkarian et al., 2017). Administrators must decide whether to maintain the status quo, namely a transactional form of advising, or invest in models that utilize staff college-wide, faculty, and technology to fill the gaps (Achieving the Dream, 2018; Donaldson et al., 2016; Drake, 2011; Kalamkarian et al., 2017). Once colleges have made an investment, advisors can do more than transmit knowledge; they can focus on facilitating academic integration (Achieving the Dream, 2018; Donaldson et al., 2016; Lema & Agrusa, 2019). A holistic student approach gives the flexibility to address each student's unique needs from institution to institution, thus increasing the likelihood students will be retained (Achieving the Dream, 2018; Drake, 2011; Kardash, 2020; Lynch & Lungrin, 2018).

Principles of Adult Learning

The faculty's primary role is to ensure students are learning, regardless of academic barriers students face (Bailey et al., 2015). The core adult learning principles of andragogy were designed by Knowles et al. (2012) to be applied by faculty to all adult learning situations; therefore, they are ideal to ensure students are learning. The principles include the learner's need to know, self-concept of the learner, prior experience of the learner, readiness to learn, orientation to learning, and motivation to learn (Knowles et al., 2012). Researchers refer to the community college student demographic as intergenerational (Barcinas et al., 2016; Thompson, 2018). The principles of andragogy provide the flexibility to assist all learners in this category (Knowles et al., 2012). If students are to stay on their designated path, faculty and student support staff must ensure students are learning. If designed correctly, Guided Pathways programming can accomplish this task. The following sections outline examples of how programming can incorporate principles of adult learning by addressing learning strategies, purpose and relevance, and motivation.

Learning strategies. To foster an environment of growth, faculty and staff should apply adult learning theories and corresponding strategies to courses and supports. The Guided Pathways model includes courses in traditional subjects such as math, English, and science, as well as including non-traditional supports in the form of orientations, workshops, and individualized programming as part of the pathway. Drago-Severson and Blum-Destefano (2018) describe the potential effects stating, "when adults in schools have the personal and organizational support to grow, they can bring their best selves to their students, families, and peers" (p. 23). They further explain the impact as "cultivating school communities that are growth enhancing … that has been linked to improved student achievement and outcomes" (p. 23). The application of adult learning theory in and out of the classroom affords students the opportunity for success as they navigate their educational pathway.

When considering the application, van der Walt (2019) posed the question "whether self-directed learning is a characteristic of learners or whether it should be regarded as a goal of educators to help learners become self-directed" (p. 2). According to his research, truth can be found in both statements (van der Walt, 2019). Adult learners already possess the ability to self-direct their educational experience based on personality, prior involvement, or other factors. Even though adult learners, particularly younger adult learners, may have been conditioned to seek knowledge from others, having rarely been given the opportunity to explore solutions on their own. Thus, educators could foster growth in this area.

In line with the Guided Pathways model of addressing student success, learning strategies should be applied throughout their educational experience and not just reserved for traditional classes. Success staff can accomplish this using differentiated coaching, an adaptation of differentiated instruction (Merriam & Bierema, 2014). Providing breakout sessions in a new student orientation gives the student autonomy in their learning (National Academies of Sciences, Engineering, and Medicine, 2018). Group academic coaching sessions provide opportunities for collaboration and metacognition (National Academies of Sciences, Engineering, and Medicine, 2018). By combining the principles of adult learning with learning strategies and reinforcing them throughout the pathway, students will have the opportunity to grow in their capacity to learn.

Purpose and relevance. Following the Guided Pathways model, academic advisors address a student's career goals from the time of entering college through completion. The task is to help the student make specific connections to what they are learning, their current lives, and a bigger purpose (Hulleman & Happel, 2018). However, this goes beyond student behaviors to include developing specific beliefs in students. This belief is in purpose and relevance to one's life and life goals instead of placing value only for a grade (Hulleman & Happel, 2018). Ideally, student success staff will reinforce these behaviors and beliefs that the instructor has already introduced.

As students embark on their journey to complete their designated degree, advisors should instill purpose and relevance through their interactions in success programming.

To cultivate purpose, advisors can encourage students to reflect on how attending college reflects their core values (Hulleman & Happel, 2018). Such an exercise will help students think about and develop their why. Students can connect what they are learning to what is important in their life. This strategy aligns with the adult learning principle of knowing why and instilling motivation to continue on their path to success.

Motivation. Many students enter college with a purpose; however, that purpose is not always clearly defined or understood. If students can identify and define their "why," they have a greater chance of following their plan to achieve their educational goals. Merriam and Bierema (2014) outline Raymond Wlodkowski's integrated levels of adult motivation that build on adult learner assumptions and being culturally responsive. These include establishing inclusion, developing attitude, enhancing meaning, and engendering confidence (Merriam & Bierema, 2014). Success staff can incorporate many of these strategies into student success programming in addition to the classroom.

A program designed to help a student on academic probation return to good academic standing is a primary example of a curriculum that has the capacity to incorporate motivational strategies. Each student's expectations, needs, goals, and previous experiences are key factors to address in the first appointment (Merriam & Bierema, 2014). Differentiated coaching could be applied when recommending actions to the student. This approach includes planning time on tasks, scaffolding strategies for challenging content, discussing effort and the potential impact, and general encouragement (Merriam & Bierema, 2014). Accountability, feedback, and the transfer of learning are examples of strategies more appropriate for subsequent appointments (Merriam & Bierema, 2014). To be most effective, instructors and student support staff need to work together to provide students with the support they need to stay motivated and realize achievement (Burt et al., 2013).

By aligning strategies, student support staff and instructors can ensure learning is occurring each step of the pathway. Knowles et al. (2012) stated it best, “andragogy focuses on the learning transaction, as opposed to the overall goal for which the program is offered” (p. 149). This statement speaks to the applicability of using adult learning principles in and out of the classroom, facilitating academic integration.

Motivational Interviewing

To be more holistic, success staff must dig into the issues students face both academically and socially. However, it can be challenging to encourage a student to share such information as the relationship is developing. Motivational interviewing is a clinical counseling technique recently adapted by Schiemann and Molnar (2020) to be used in academic settings. The proposed technique begins with building rapport and using active listening skills to allow the students to express their feelings (Schiemann & Molnar, 2020). Following this step is the Transtheoretical Model of Change (Hoeger et al., 2017) to determine in what stage a student falls, thus allowing the student success staff member to adjust their approach. Motivational interviewing applies five steps: empathy, develop discrepancy, avoid argument and confrontation, roll with resistance, support self-efficacy, and optimism (Schiemann & Molnar, 2020). This technique is ideal for determining what barriers a student may be facing, their primary career interests, or other important factors to their success.

The above aspects of holistic advising, adult learning principles, and motivational interviewing, when combined with probation programming, wellness support, academic coaching, and academic advising, form a complex approach to student success programming grounded in differentiated coaching.

Conclusion

I applied complexity theory to target academic integration through Guided Pathways, arguing that the framework is a complex adaptive system where the whole is greater than the sum of its parts (Davis & Simmt, 2016). When designed well by college administrators, the complex system has the ability to adapt as things shift and change. Davis et al. (2012) explains this as planned but not predetermined, meaning the process to achieve outcomes may vary. The pillars of the Guided Pathways model encapsulate a successful approach to student retention, and the sum of it is greater than each part. Academic integration is a complex concept as well, involving academic advising, probation programming, wellness support, academic coaching, holistic advising, principles of adult learning, and motivational interviewing. These aspects are brought together to form differentiated coaching described and evaluated in this study.

Theoretical Framework

I combined theories to develop a theoretical framework that focuses on the student's end goals while providing the immediate, individualized support needed to achieve these goals. The framework was grounded in an approach called differentiated coaching. Differentiated coaching was adapted from the instructional method of differentiated instruction in which teachers take multiple approaches to content, process, and product while considering student readiness, interest, and learning (Tomlinson, 2017). I used the term "coaching" to explain the process through which development occurs, rather than advising, which is narrower in its focus. Coaching is applied by student success staff across programming, in contrast to advising that specifically applies to academic planning.

For purposes of this study, “academic integration” is defined by Latz (2015) as interactions that occur because of academic enrollment. Integration includes the student’s connections through participation in classroom activities and student support service programming (Latz, 2015). Through differentiated coaching, students are offered academic integration as a complex adaptive system that conforms to their needs. Participation in this complex adaptive system has the potential to increase a student’s likelihood to return to the college the following semester (Tinto, 1993). Revisiting the two pillars of Guided Pathways reveals further evidence of a complex adaptive system delivering academic integration opportunities.

The Guided Pathways model only includes suggestions for the classroom. This framework expands these experiences to also include student success programming, hence the use of academic integration as a foundational component. When college administrators design the first pillar, helping students stay on their path, support for students should be embedded along the pathway and be continuous to help students make informed choices (Jenkins, Lahr, et al., 2018). Once a pathway is selected, student success staff should create an academic plan, monitor student progress, and provide feedback or interventions when the student veers off-track (Jenkins, Lahr, et al., 2018). Additionally, student success staff promote learning and assistance through academic integration both in and out of the classroom. The second pillar, ensure students are learning, focuses on life-ready learning (Perkins, 2014) by encouraging the inclusion of experiential and collaborative learning approaches (Jenkins, Lahr, et al., 2018; National

Academies of Sciences, Engineering, and Medicine, 2018). Additionally, there is a need to align course learning outcomes with the requirements for successful employment (Jenkins, Lahr, et al., 2018). The two pillars emphasized in this study expand on the model initially developed and interpreted by success experts to include a broader scope of academic integration and thus student support.

Conclusion: Purpose of the Study

The purpose of this quantitative study was to test a Guided Pathways framework positioned in a complex adaptive system to determine the relationship between differentiated coaching, as deployed in student success programming through the Guided Pathways initiative, and retention for associate degree seeking or general transfer students who have completed at least thirty credit hours at Chaparral Community College. The study also included research-based variables (i.e., cumulative grade point average, cumulative credit hours earned, enrollment status), which have shown to relate to retention, as predictors in the analysis. The independent variable, differentiated coaching, was defined as considering a student's interests, goals, and abilities, both personal and academic, when planning to reach educational goals (Kardash, 2020; Tomlinson, 2017). I defined the dependent variable as student retention from semester to semester. Finally, intervening variables (e.g., success program delivery mode [altered since Covid-19], success coach personality) were variables that may transmit the effect of differentiated coaching on student persistence (Creswell & Creswell, 2018).

The findings of this study inform community college leaders who are working on designing Guided Pathways at their institutions. Differentiated coaching offers an approach to academic integration that encourages a complex perspective, and evidence supports this approach. The following chapter details the research design and methodology of this quantitative study.

CHAPTER TWO

Methodology

Introduction: Research Questions

The previous chapter described how a complex perspective on a student success initiative could be used to address community college retention. By employing "both/and" logic, student success relies on experiences both in and out of the classroom. A student cannot persist toward meeting their educational goals if they are not learning. By taking a complex adaptive system approach (Davis et al., 2012; Holland, 2014; Mitchell, 2009) to the two Guided Pathways pillars—help students stay on their path and ensure students are learning—success programming can meet individual student needs. Differentiated coaching (Tomlinson, 2017) is the method applied as a complex perspective on student success programming.

A quasi-experimental quantitative design lends itself to exploring the relationship between these two groups. Specifically, this study investigated the use of differentiated coaching with community college students—who were associate degree seeking or general transfer, non-dual credit with at least 30 credit hours—in student success programming through the Guided Pathways initiative. Specifically, the following hypotheses informed the approach:

- H_0: There is no relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention for semester one to semester two (Y).
- H_1: There is a relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention from semester one to semester two (Y).

- H_0: There is no relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention from semester one to semester three (Y).
- H_2: There is a relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention from semester one to semester three (Y).

Researcher Perspective and Positionality

My overarching worldview is postpositivism in that the study intends to determine the causes that influence the outcome (Creswell & Creswell, 2018). I explore the relationship between a complex method applied through Guided Pathways and retaining students at a community college. Aljohani (2016) outlines many theories that explain student retention in four-year institutions of higher education. However, it is essential to consider the student experience through academic integration at the community college level both in and out of the classroom (Latz, 2015; Tinto, 1993). How a student experiences academic integration is critical when implementing an intentional model such as Guided Pathways. Each element of the pathway, including student characteristics, have been independently researched to some degree. However, the intentional design of Guided Pathways considers all programming together specific to the needs of a community college and, therefore, a group of students (Jenkins et al., 2019). It makes sense to take a complex perspective (Davis et al., 2012; Holland, 2014; Mitchell, 2009) on academic integration. This quantitative study examines the complex relationship between differentiated coaching and retention (Field, 2018).

My professional context is a community college administrator tasked with ensuring students' successful completion of their educational goals. Bailey et al. (2015) argued that community colleges could not design program interventions in isolation to positively impact student retention and successful completion. For this reason, the Texas Success Center and American Community College Association outlined a more comprehensive model termed Guided Pathways (Jenkins et al., 2019). This model calls for a college redesign that supports collaboration in planning and implementation (Jenkins et al., 2019). I believe that student success administrators should structure the programs available to support students (e.g., academic advising, academic coaching, probation programming, wellness support) to facilitate learning in the classroom. Facilitating learning connects students academically and socially, which increases levels of academic integration (Tinto, 1993) and therefore increases retention or helping students stay on the path (Jenkins, Lahr, et al., 2018).

In the 15 years of working in the community college realm of higher education, I observed that the responsibility for student success had shifted back and forth between the college's instructional services and student services components. I began my tenure on the instruction side, tasked with an initiative to help instructors incorporate technology in the classroom to increase student engagement. For the past five years, I have been responsible for carrying out the initiatives of a Title III Strengthening Institutions grant designed to increase retention and graduation rates. These initiatives included student success programming targeting “at-risk” student populations. Based on the outcomes of these programs, I noted that program administrators have left out a student group, students in “the middle” who have completed at least 30 credit hours.

As student success administrators define Guided Pathways at my institution, questions remain about the effectiveness of this intentionally designed, collaborative, college-wide initiative on student retention leading to the successful completion of educational goals. A quasi-experimental quantitative design lends itself to exploring the relationship of differentiated coaching, as deployed in student success programming through the Guided Pathways initiative, and retention (Field, 2018) for general transfer students who have completed at least 30 credit hours at a community college.

Theoretical Framework Application

Differentiated coaching is an approach that focuses on the needs of the student to provide the appropriate support service. The facets of this framework are interrelated and work together using "inclusive-or" logic (Aoki, 2004; Pratt, 2008a) to move students toward academic integration (Latz, 2015). The differentiated coaching approach is a complex adaptive system that responds and adapts to outside factors (Davis et al., 2012; David & Simmt, 2016; Holland, 2014; Mitchell, 2009) by articulating a network of relations among academic advising, probation programming, wellness support, academic coaching, holistic advising, motivational interviewing, and principles of adult learning as they relate to supporting students on the path and remain engaged in learning. Through the lens of differentiated coaching, student success advisors assess the needs of the student and apply any combination of the seven facets to further the student's educational goals. This application of supports helps move the student toward academic integration.

The differentiated coaching approach is grounded in the two pillars of the Guided Pathways framework leading to the research questions in which I seek to find the relationship between the use of differentiated coaching and semester one to semester two and semester one to semester three student retention rates. Using the two pillars, helping students stay on their path and ensure students are learning, the Guided Pathways framework situates this intervention as a whole greater than the sum of its parts. The research question frames an initial investigation into this novel approach to academic integration that is broader in scope to determine its influence on student retention for students who have earned 30 or more credit hours.

This study also included a preliminary correlation analysis to examine the three student predictor variables that may also have a relationship to semester one to two and semester one to three retention. These student predictor variables have been shown to have a relationship to retention in past studies (Metz, 2004; Okun et al., 1996; Schwebel et al., 2012; Tinto, 1993). The correlation analyses demonstrated that Chaparral Community College students were consistent with historical findings. The predictor variable cumulative grade point average is a measure of achievement and corresponds to the ensuring students are learning pillar. Cumulative credit hours earned and enrollment status measures time to completion, aligning with the pillar helping students stay on their path. These three are included as predictor variables to determine if the differentiated coaching-retention relationship is genuine and not due to other factors (Metz, 2004; Okun et al., 1996; Schwebel et al., 2012; Tinto, 1993).

The theoretical framework forms the treatment of differentiated coaching to increase academic integration through Guided Pathways. To research this increase, I selected two cohorts of students to analyze student retention before and after advisors applied the differentiated coaching framework to student meetings. The first cohort began with students enrolled in the Fall 2018 semester. Choosing this semester allowed time to follow the students for three semesters before applying the treatment. The second cohort began in the Fall 2020 semester, with the first group of enrolled students receiving student success programming that drew on the differentiated coaching approach. I tracked this cohort for three semesters concluding in the Fall 2021 semester at the census date. This data collection was robust enough to run the analysis needed to determine the relationship between treatment and student retention.

The control and treatment groups were used as a predictor that allowed me to isolate the relationship of each group to the outcome of retained or not retained, holding all other variables constant. The use of differentiated coaching was the difference between the two groups, and this approach was informed by the application of student success advisors engaging in the seven facets as needed to assist students in meeting their educational goals. Due to the structure of the dependent variable, I used binary logistic regression models to predict membership of only two categories, retained or not retained. Data from the control and the treatment groups were mutually exclusive, so the use of differentiated coaching could be the difference between the results of retention rates. This is possible as a dichotomous predictor provides the numerical relationship between differentiated coaching and retention compared to the control group.

Research Design and Rationale

I designed this study to determine the relationship between differentiated coaching, as deployed in student success programming through the Guided Pathways initiative, cumulative grade point average, cumulative credit hours earned, and enrollment status and semester-to-semester retention rates of sophomore, associate degree seeking or general transfer, non-dual credit students who completed at least 30 credit hours at a community college. Because retention is reported by fall semester to fall semester to state agencies, the hypotheses included consideration of fall to spring semesters as well as fall to fall semesters. The following hypotheses guided the study.

- H_0: There is no relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention for semester one to semester two (Y).
- H_1: There is a relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention from semester one to semester two (Y).
- H_0: There is no relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention from semester one to semester three (Y).
- H_2: There is a relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention from semester one to semester three (Y).

To appropriately answer the hypotheses, I instituted a quasi-experimental quantitative design using binary logistic regression (Creswell & Creswell, 2018; Field, 2018). I chose a logistic regression model because the outcome or dependent variable, retention, is dichotomous (Field, 2018). This model allows for predicting to which category a participant belongs, based on their predictor variable scores (Field, 2018). In other words, what are the odds a student will be retained given their scores on the dichotomous variable, differentiated coaching (group), or their cumulative grade point average, cumulative credit hours earned, and enrollment status?

The differentiated coaching approach served as a framework for training student success advisors to deliver the treatment to students. The student success director built teams to support students across success programming in order to differentiate where to engage. Student success advisors received online training, due to Covid-19 restrictions, in holistic advising, adult learning principles, and motivational interviewing. This training laid the foundation for determining how to engage students based on their individual needs. The student success director aligned and embedded the principles and theories throughout the advising process to ensure the treatment was applied consistently.

Site Selection and Population Sampling

In response to the problem of community college students completing degrees at a low rate, I chose a specific site and population as my focus. In the following paragraphs, I describe the designated site and reasons for selection. I conclude with the population parameters and detail the data sample collected.

Site

I utilized a single site to study the effect of differentiated coaching deployed in student success programming through the Guided Pathways initiative on retention. More specifically, students had to be enrolled in Chaparral Community College as of the official census date. Chaparral Community College was selected as a "backyard" site (Creswell & Poth, 2018), as each community college has unique processes and services along these Guided Pathways. My interests lay in studying the treatment deployed at my current place of employment, Chaparral Community College. Due to the lack of transferability of experiences between colleges, I believed this site was the most beneficial to the study. Backyard sites were further examined in a study by Latz (2015), noting the general application of attrition models across institutions showed varying results, in part due to the uniqueness of each institution. For this reason, she suggested institutions shift to focus their research locally (Latz, 2015).

Chaparral Community College is a rural two-year institution located in the southwestern region of the United States. The College meets the educational needs for a twelve-county service area by offering five associate degrees, eleven associate of applied science degrees, and seventeen career and technical education certificates (Chaparral Community College, 2019). The institution averages 33% of students enrolling part-time with less than twelve credit hours and 67% of students enrolling full-time (Chaparral Community College, 2019, 2020, 2021). The average student age is twenty-three years old, and the student to faculty ratio is consistently eighteen to one (Chaparral Community College, 2019, 2020, 2021).

Enrollment has seen a 22% decline over the last five years: 3,016 students enrolled Fall 2017, 3,055 students enrolled Fall 2018, 2,933 students enrolled Fall 2019, 2,786 students enrolled Fall 2020, and 2,362 students enrolled Fall 2021 (Chaparral Community College, 2019, 2020, 2021). Table 2.1 displays the trends of enrollment over the last five years. The fall term is used to report census data to the state agency.

Table 2.1

Trends of Enrollment for Chaparral Community College

Term	Enrollment
Fall 2017	3,016
Fall 2018	3,055
Fall 2019	2,933
Fall 2020	2,786
Fall 2021	2,362

Population Sampling

This study's population was defined as a target population because data was available for a specific segment of the population (Creswell & Creswell, 2018). This study specifically investigated all enrolled students who were considered sophomores. To measure retention over enough time, I determined that the population consisted of students who met four criteria: classified as associate degree seeking or general transfer, non-dual credit, completed a minimum of 30 cumulative credit hours, and had not completed a degree or certificate to qualify for the study. At this site, associate degree seeking students plan to complete an Associate of Arts, Associate of Science, or Associate of Arts in Teaching degree. General transfer is defined as those students who intend to transfer to a four-year institution of higher education.

I sampled two groups to create a control “pre-treatment” group and a treatment “post-treatment” group. First, I selected the control group to include Chaparral Community College students who enrolled in and completed coursework in the Fall 2018 semester (i.e., Fall 16-week semester, Fall I eight-week term, or Fall II eight-week term). For this category, 1,459 students were classified as associate degree seeking or general transfer and non-dual credit, with 585 students with at least 30 credit hours earned having not previously earned a degree or certificate. Second, for the treatment group, I selected Chaparral Community College students who enrolled in and completed coursework in the Fall 2020 semester (i.e., Fall 16-week semester, Fall I eight-week term, or Fall II eight-week term). Following this sort, I identified 1,341 students classified as associate degree seeking or general transfer and non-dual credit. Then, each student must have completed a minimum of 30 cumulative credit hours and not previously completed a degree or certificate to qualify for the study. This process left 465 students whom I selected to be included in the treatment group. Finally, to ensure participants belonged to only one group, I removed duplicate students enrolled in the Fall 2018 semester and the Fall 2020 semester. These students remained coded as Fall 2018 participants, bringing the total to 1,050 participants (See Table 2.2.).

Table 2.2

Population Size by Group

Measure	Group 1 (control group)	Group 2 (treatment group)
Population	$N = 585$	$N = 465$

Data Collection Procedures

In this section, I define the data points and explain the location of each including who at Chaparral Community College were responsible for mining the information. Next, I outline the process for extracting and preparing the defined information for analysis. Lastly, I review the data storage and reporting processes for Chaparral Community College.

I extracted institutional student data, both demographic and academic, from the student information system to Microsoft Excel via file transfer protocol (FTP). Demographic data consisted of enrollment status (i.e., part-time, full-time). Academic data contained the first term of enrollment, dual credit status, major, semester grade point average, cumulative grade point average, cumulative credit hours earned, number of credits enrolled, and degree completion. The College registrar provided graduation data for each year requested from the Texas Higher Education Coordinating Board graduation/completion report, titled CBM009, and transfer data from the National Student Clearinghouse student tracker data services for the 2019 and 2021 calendar years. Once the data was in Microsoft Excel, I used the filtering and sorting functions to identify the target participants for both the control and treatment groups. The student information system is a data warehouse and does not have reporting analytics standard in newer systems. For this reason, several data points are necessary to ensure accurate information for analysis in Microsoft Excel and SPSS (*v*.28). I requested permission to access institutional student data at the same time as the site request.

The registrar at Chaparral Community College consistently “freezes” data at two distinct points in time each semester, the census date and the date final grades post to the student information system. To ensure validity and reliability (Creswell & Creswell, 2018; Creswell & Plano Clark, 2018), I requested the datasets from both points in time for the Fall 2018, Spring 2019, Fall 2019, Fall 2020, Spring 2021, and Fall 2021 semesters. Chaparral Community College uses these data points to report to state and national governance agencies (e.g., Texas Higher Education Coordinating Board, Integrated Postsecondary Education Data System (IPEDS), Southern Association of Colleges and Schools Commission on Colleges). This method of data collection creates consistency across terms as well as across institutions.

The primary data points used in this study were retention, cumulative grade point average, number of cumulative credit hours earned at specified points in time, enrollment status at specified points in time, and the control or treatment group. For the purpose of this study, I defined retention as a participant who met one of the three possible conditions: completed a semester and subsequently enrolled in courses the following semester (Tinto, 1993), completed a degree or certificate, or transferred to another two- or four-year institution. I computed retention by comparing the cohort of students who completed the semester, as evidenced by the final posting of grades, and student enrollment the following semester, as evidenced by enrollment reported on the census date. I then compared the same cohort of students to the Texas Higher Education

Coordinating Board graduation/completion report and transfer report from the National Student Clearinghouse.

Based on the data collected, cumulative grade point average, number of cumulative credit hours earned, and enrollment status were also used as predictor variables to determine the relationship to retention. The differentiated coaching approach began in the Fall 2020 semester; thus, the data were separated into a control group and a treatment group to compare retention rates. Secondary data points included participant demographics and were used during analysis to identify themes to be addressed in future studies.

Data Analysis Procedures

The first portion of this section explains the steps I followed to prepare data for analysis using Microsoft Excel and Access. Then I describe the steps taken in SPSS (*v.*28) to label and code the variables. Next, I perform binary logistic regression analysis and the framework that supports this analysis. I outline each test in the order I carried out the functions.

Preparing the Data

Before the data could be analyzed, I identified and coded the independent, dependent, and predictor variables using the features available in Microsoft Excel and Microsoft Access. I utilized Microsoft Excel to store each dataset, convert raw data into identified variables, filter, and sort to prepare for coding, code categorical variables, unduplicated participants, and maintain the integrity of the data using tabs at each point in the manipulation process (see Figure 2.1). Microsoft Access was my chosen tool to compare datasets to determine the dependent variable, retention. I also merged data in separate Microsoft Excel spreadsheets using Microsoft Access as each variable was added to the dataset. I was able to maintain the integrity of the data by keeping the dataset format intact using the features in Microsoft Access and then exporting them back to Microsoft Excel as a separate sheet (see Figure 2.1).

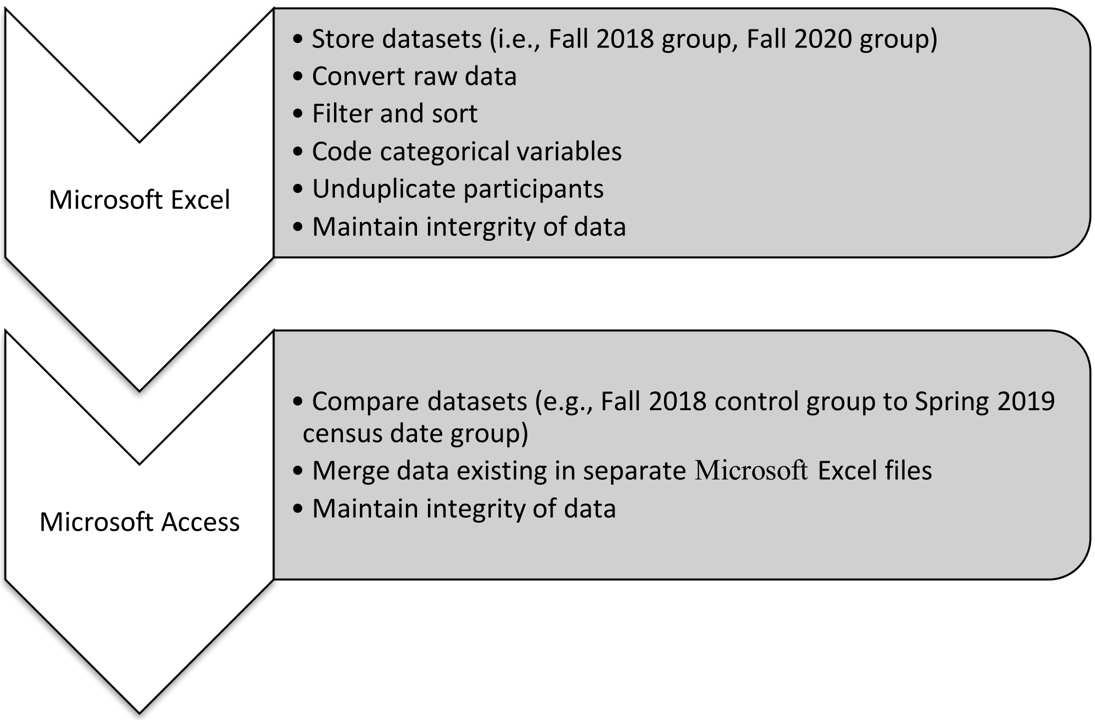


Figure 2.1. Data manipulation process prior to SPSS (*v.*28).

The student information system used by Chaparral Community College had a few limitations in that data could not be extracted in the exact format requested. This limitation led to the need to filter, sort, and manipulate the data using Microsoft Excel and Microsoft Access to code the variables appropriately prior to entering the data into SPSS (*v.*28). Using Microsoft Excel, I labeled all student course enrollment data, as exported from the student information system, "ALL" to preserve the original dataset. I then created a second tab labeled "UnDup" and unduplicated the data by student ID using the data tool, remove duplicates. Next, the data were filtered to include only academic transfer majors using the field "major" and pasted into a new tab labeled appropriately. After that, data were filtered to remove dual credit students using the field "dualcredit." The final step to prepare the dataset for the coding of variables was to use Microsoft Access to remove students who had previously completed a certificate or degree. For consistency, I repeated this process for the Fall 2018 and Fall 2020 with final grades datasets which were represented in separate spreadsheets.

Next, I performed the following steps using Microsoft Excel to code the variables for the Fall 2018 control cohort and the Fall 2020 treatment cohort using the final grades datasets. To code enrollment status, a categorical variable, I created a separate column titled "enrollment status." First, I filtered for current credits enrolled, meaning the number of credit hours the student was enrolled in that semester (i.e., Fall 16-week semester, Fall I eight-week term, or Fall II eight-week term). Then I used the column with the field name "creditload" to include only students enrolled in 1–11 credit hours. I placed a 0 in the corresponding cell in the column titled "enrollment status" to represent part-time enrollment. I then filtered to include only students enrolled in 12 or more credit hours and inserted a 2 in the corresponding cell in the "enrollment status" column signifying full-time enrollment.

The independent variable designating students as receiving treatment or not receiving treatment was categorical and needed to be coded as such. To designate students in the control or the treatment group, I inserted a column titled "group" on each dataset spreadsheet, titled Fall 2018 and Fall 2020 (final grades datasets). I coded all students in the Fall 2018 dataset with a 0 to indicate control group. For students in the

Fall 2020 group, I inserted a 1 in the "group" column, signifying treatment group. The remaining variables, cumulative grade point average and cumulative credit hours earned, were continuous and therefore were coded appropriately without manipulation.

To determine the dependent variable, retention, I referenced several data sources (e.g., Fall 2018 group, Fall 2020 group, retained to following semester, the Graduation/Completion Report, the Transfer Report). Since data existed on multiple spreadsheets, I utilized Microsoft Access to merge and compare datasets. Retention was realized if the student was enrolled in the subsequent term, earned a degree, or successfully transferred to another higher education institution. Each of these retention variables was coded twice, from fall to spring and from fall to fall.

I performed the following steps to determine retained or not retained for each student in the Fall 2018 and Fall 2020 groups. To determine "retained to spring semester," I uploaded the Fall 2018 group final grades and Spring 2019 census date datasets into Microsoft Access. I then created a query to compare the two datasets to determine which students who received grades in the Fall 2018 were also enrolled in classes as of the census date in the Spring 2019 semester. To maintain the integrity of the datasets, I selected all column field names included in the Fall 2018 group and ran the query. I saved the resulting dataset and exported the information back to Microsoft Excel. Once in Microsoft Excel, I created a column titled "retain to SP19" and coded each student retained as a 1. I then coded each student not retained as a 0. I repeated this process using the Fall 2020 group final grades and Spring 2021 census datasets.

The second retention variable to consider was "retained to fall semester." This was created because the data reported to state agencies included enrollment in one fall to the next fall term. I uploaded the Fall 2018 group final grades and Fall 2019 census date datasets into Microsoft Access. I then created a query to compare the two datasets to identify students who completed their coursework in the Fall 2018 and also enrolled in classes as of the census date in the Fall 2019 semester. I selected all column field names included in the Fall 2018 group to maintain the integrity of the datasets and ran the query. I saved the resulting dataset and exported the information back to Microsoft Excel. Once in Microsoft Excel, I created a column titled "retain to FA19" and coded each student retained as a 1. I then coded each student not retained as a 0. I repeated this process using the Fall 2020 group final grades and Fall 2021 census datasets.

The third retention variable to calculate was "semester one degree completion." I imported the Fall 2018 group final grades and Fall 2018 graduation/completion datasets into Microsoft Access. I then created a query to compare the two datasets to determine which students who completed coursework in the Fall 2018 also completed a degree at the conclusion of the Fall 2018 semester. To maintain the integrity of the datasets, I selected all column field names included in the Fall 2018 group and ran the query. I saved the resulting dataset and exported the information back to Microsoft Excel. Once in Microsoft Excel, I created a column titled "retain grad FA18" and coded each student completing a degree as a 1 indicating retained. I then coded each student not completing a degree 0, showing they were not part of the retention category of graduation. I repeated this process using the Fall 2020 group final grades and Fall 2020 graduation/completion datasets.

Fourth, I determined the retention variable "semester two degree completion" by importing the Fall 2018 group final grades and Spring 2019 graduation/completion datasets into Microsoft Access. I created a query comparing the two datasets to determine which students who completed coursework in the Fall 2018 also completed a degree after the Spring 2019 semester, which extended through August. I saved the results and exported the information back to Microsoft Excel. Once in Microsoft Excel, I created a column titled “retain grad SP19” and coded each student completing a degree as a 1 indicating retained. I then coded each student not completing a degree 0, signifying not retained. I repeated this process using the Fall 2020 group final grades and Spring 2021 graduation/completion datasets.

Fifth, I computed the retention variable “semester one transfer.” Using Microsoft Access, I imported the Fall 2018 group final grades and Spring 2019 transfer datasets. I created a query comparing the two datasets to determine which students who completed coursework in the Fall 2018 transferred to another institution in the Spring 2019 semester. I saved the results and exported the information back to Microsoft Excel. Once in Microsoft Excel, I created a column titled “retain transfer SP19” and coded each student who transferred as retained by inputting a 1. I then coded each student not transferring as not retained by inputting a 0. I repeated this process using the Fall 2020 group final grades and Spring 2021 transfer datasets.

The sixth and final retention variable to compute was “semester two transfer.” Using Microsoft Access, I imported the Fall 2018 group final grades and Fall 2019 transfer datasets. I created a query comparing the two datasets to determine which students who completed coursework in the Fall 2018 transferred to another institution in the Fall 2019 semester. I saved the results and exported the information back to Microsoft Excel. Once in Microsoft Excel, I created a column titled “retain transfer FA19” and coded each student who transferred as retained by inputting a 1. I then coded each student not transferring as not retained by inputting a 0. I repeated this process using the Fall 2020 group final grades and Fall 2021 transfer datasets.

Labeling and Coding the Data

The dependent variable in this study was a single dichotomous variable, retention. To calculate a single variable required that I merge the retention variables above into an overall determination of retained for both Spring and Fall for each student. To do this, I combined the previously determined retention variables, retained to spring semester, semester one degree completion, and semester one transfer, into one "overall retained fall to spring" column. For purposes of this calculation, I used an "or" logic to ensure a student was not counted twice. I determined a student to be "overall retained fall to spring" if they were coded as a 1 in any of the three variables. I used the same logic to calculate "overall retained fall to fall" using the three variables retained to fall semester, semester two degree completion, and semester two transfer. The remaining variables, cumulative grade point average and cumulative credit hours earned (using the final grades datasets for Fall 2018 and Fall 2020), were continuous and therefore were coded appropriately without manipulation.

After I filtered, sorted, and manipulated the data in Microsoft Excel and Microsoft Access, they were entered into SPSS (*v.*28) for statistical analysis. I then labeled and coded the data, removing names and corresponding student identification numbers (Creswell & Creswell, 2018; Creswell & Plano-Clark, 2018). I selected a logistic regression analysis because of the ability to predict categorical outcomes from both categorical and continuous predictor variables (Field, 2018). I began the data analysis procedure by assigning numeric values to each categorical variable in SPSS (*v*.28). Subsequently, I cleaned the database to locate and correct or eliminate errors (Creswell & Plano-Clark, 2018). Finally, each variable was named and defined using the variable view tab in SPSS (*v*.28).

Performing Binary Logistic Regression Analysis

Due to the structure of the dependent variable, I used a binary logistic regression model to predict membership of only two categories, retained or not retained (Chatterjee et al., 2018; Field, 2018) and set the α at 0.05. The independent variable was the application of differentiated coaching (see Table 2.1), as deployed in student success programming through the Guided Pathways initiative. Group one contained students who completed the Fall 2018 semester before the differentiated coaching treatment was available. Group two consisted of students who completed the Fall 2020 semester after the implementation of differentiated coaching. To be ethical to all participants, I applied the intervention to all students in the treatment group. The three predictor variables, cumulative grade point average, cumulative credit hours earned, and enrollment status (see Table 2.1) were selected based on existing research (Metz, 2004; Okun et al., 1996; Schwebel et al., 2012; Tinto, 1993), accessibility of data, and their application to the two pillars of Guided Pathways. Although I could include many other predictors in the model based on previous research, the study's focus was the differentiated coaching approach to increase academic integration. Therefore, I chose to include three additional predictor variables as leveling variables.

To determine fit, I built different logistic regression models (Field, 2018). To do this, I ran an analysis in SPSS (*v*.28), and the diagnostic statistics were reviewed for signs of bias (e.g., outliers) and to check for linearity of the logit and multicollinearity (Field, 2018).

Table 2.1

Description of Variables

Variable Type	Variable Name	Variable Description	Variable Coding
Dependent	Retention	Retained by enrolling in subsequent term(s), completion of degree or certificate, or transfer	0 = Not Retained 1 = Retained
Independent	Group	Control—group of students completing Fall 2018 semester not receiving differentiated coaching; Treatment—group of students completing Fall 2020 semester receiving differentiated coaching	0 = Control 1 = Treatment
Predictor	Cumulative Grade Point Average	Cumulative grade point average at completion of cohort semester	Continuous 0.00-4.00
Predictor	Cumulative Credit Hours Earned	Number of cumulative credit hours earned at completion of cohort semester	Continuous beginning ≥ 30 credit hours earned
Predictor	Enrollment Status	Enrollment status at completion of cohort semester (full-time ≥ 12 credit hours)	0 = Part-Time 1 = Full-Time

Since the outcome of retention is categorical, I used binary logistic regression as represented by the following equation (Field, 2018, p. 643). P is the probability of γ occurring from known values of x, b_0 is the value of the outcome when the predictors are zero, and b_i quantifies the relationship between each predictor and outcome (Field, 2018).

$$P(\gamma) = \frac{1}{1+e^{-(b_0+b_1x_{1i}+b_2x_{2i}+b_3x_{3i})}}$$

$$P(\text{Retention}) = \frac{1}{1+e^{-(b_0+b_1 Holistic\ Advising_{1i}+b_2 Credit\ Hours_{2i}+b_3 Age_{3i})}}$$

Second, I used the log-likelihood statistic to assess the fit of the model. According to Field (2018), this equation sums "the probabilities associated with the predicted, $P(\gamma_i)$, and actual γ_i, outcomes" (p. 644). For each participant, the predicted γ will either be zero (there is no chance retention did occur) or one (there is a high chance retention did occur).

Log-likelihood = $\sum_{i=1}^{N}\left[\gamma_i ln\left(P(\gamma_i)\right) + 1 - \gamma_i\right)\ln\,(1 - P(\gamma_i))]$

Third, I used the Wald statistic to assess the individual contribution of the predictors (Field, 2018). The Wald statistic produces a *z*-statistic converted by SPSS (*v*.28) to a chi-square distribution. Lastly, the odds ratio exp(*B*) is essential to interpreting the logistic regression. In this study, the odds ratio represents the ratio of being retained after a unit change in the predictor variable to the odds of being retained without treatment (Field, 2018, p. 646).

Odds ratio = $\frac{odds\ after\ a\ unit\ change\ in\ predictor}{original\ odds}$

If the value is larger than one, then as the predictor increases, the odds of being retained increase, Conversely, if the value is less than one, then as the predictor increases, the odds of being retained decrease (Crowson, n.d.; Field, 2018).

Table 2.2 illustrates the groups for which I ran a binary logistic regression. For each group (control, treatment), binary logistic regression was run for the following terms: semester one to two and semester one to three. This process enabled me to track retention rates over a three-semester period while determining the relationship to the predictor variables.

Table 2.2

Retention Measures by Group

Semester	Group 1 (control group)	Group 2 (treatment group)
Semester 1 to 2	Fall 2018 to Spring 2019	Fall 2020 to Spring 2021
Semester 1 to 3	Fall 2018 to Fall 2019	Fall 2020 to Fall 2021

Ethical Considerations

I weaved this process throughout the design of the study, from site and population selection to data collection and analysis to interpretation and reporting of results. I began the process by following the guidelines set forth by Baylor University. An inquiry and review were submitted to the Institutional Review Board (IRB) for approval before beginning the study. After gaining approval from the Institutional Review Board, a written request was drafted and emailed to the President. The President of Chaparral Community College granted access to the site.

I obtained permission to use Chaparral Community College facilities, students, student information system, and data before beginning the study. I explained the nature of the involvement of students in the study to the college administration and committed to neutrality with no adverse or favorable treatment based on participation (Creswell & Plano-Clark, 2018). To protect anonymity and access, I collected and stored data in a secure location (Creswell & Plano-Clark, 2018). Finally, I reported all the results to create a complete picture so as not to create bias. I noted the limitations of the study, and future research was proposed.

Limitations and Delimitations

A limitation of the study was the effect of Covid-19 on community college practices. Access to participants had to be altered by the student success staff to provide additional modes of participation. The use of video conferencing technology, phone, and email gave students an alternative option for participation. Also, how some students experienced their guided pathway was atypical. This phenomenon gave a new dimension to be examined and provided more depth to the analysis.

One delimitation was the sampling of students that included only those enrolled in a specific community college. Using a backyard site typically means the results of the study are not generalizable across other community colleges. However, this study may serve as a guide for those wishing to replicate at their institution. Additionally, the study included all participants within the selection criteria classified as associate degree seeking or general transfer, non-dual credit, completed a minimum of 30 cumulative credit hours, and had not completed a degree or certificate. By narrowing the participant sample to these criteria, I omitted certain student groups. The impact of differentiated coaching on the retention of students in the omitted groups could be the focus of a subsequent study.

Conclusion

This binary logic regression quantitative study examines the relationship between the differentiated coaching approach and student retention. The purpose was to inform improvements through the design and implementation of the Guided Pathways reform. The results of this study have implications across the community college from student services to instructional services. The following chapter provides an analysis of the results and the corresponding impact of the research findings.

CHAPTER THREE

Results and Implications

Introduction

The purpose of this quantitative study was to test a Guided Pathways framework positioned in a complex adaptive system to determine the relationship between differentiated coaching, as deployed in student success programming through the Guided Pathways initiative, and retention for associate degree seeking or general transfer students who have completed at least thirty credit hours at Chaparral Community College. The study also included predictor variables (i.e., cumulative grade point average, cumulative credit hours earned, enrollment status) known to contribute to academic integration (Metz, 2004; Okun et al., 1996; Schwebel et al., 2012; Tinto, 1993) by including them in the analysis. Due to the structure of the dependent variable, I used two binary logistic regression models to predict membership of only two categories, retained or not retained (Chatterjee et al., 2018; Field, 2018). The log-likelihood statistic was applied to assess the fit or statistical significance of each model. One binary logistic regression model calculated the analysis for semester one to semester two. The second model calculated the analysis for semester one to semester three. This chapter outlines the results of these analyses in the order presented for both semester one to semester two and semester one to semester three.

Population

To effectively address the hypotheses, I determined the population would consist of students who met four criteria: classified as associate degree seeking or general transfer, enrolled as non-dual credit, completed a minimum of 30 cumulative credit hours, and had not previously earned a degree or certificate. The first criterion was based on the fact that at the site selected, students successfully completed their path at the college when they earned an associate degree or were accepted as a transfer to a four-year institution.

I sampled two groups to create a control "pre-treatment" group and a treatment "post-treatment" group. First, I selected the control group to include Chaparral Community College students who enrolled in and completed coursework in the Fall 2018 semester and who met the four criteria above. Then I identified the treatment group as Chaparral Community College students who enrolled in and completed coursework in the Fall 2020 semester and met the four criteria above. This process resulted in a total of 1,050 participants (585 control, 465 treatment).

Assumption Checking and Data Cleaning

To test the assumptions associated with a logistic regression analysis, I first visually inspected the data to ensure only two response categories to the dependent variable. Each participant had a response of zero for not retained or one for retained. This was true for both retention from semester one to semester two and retention from semester one to semester three. Second, I noted two continuous predictor variables. Cumulative grade point average contains scores ranging from 0.00 to 4.00 and cumulative credit hours earned includes hours from 30 to 216. The third assumption included an independence of observations.

The first group, control, consisted of Chaparral Community College students who were enrolled in and completed coursework in the Fall 2018 semester (i.e., Fall 16-week semester, Fall I eight-week term, or Fall II eight-week term). The second group, treatment, included students who enrolled in and completed coursework in the Fall 2020 semester (i.e., Fall 16-week semester, Fall I eight-week term, or Fall II eight-week term). To ensure participants belonged to only one group, I removed any duplicate students who appeared in the Fall 2020 semester and were also enrolled in the Fall 2018 semester. These duplicate students remained coded as Fall 2018 participants.

Finally, I calculated the logit transformation of each continuous variable (cumulative grade point average, cumulative credit hours earned) using the transform then compute variable function in SPSS (*v*.28). Once the logit variables were computed, I ran a binary logistic regression analysis by inputting the interaction between the variable and the corresponding logit variable (Field, 2018). This was conducted to determine if a linear relationship existed (see Appendix C). For the first model, semester one to semester two, the interaction term for cumulative grade point average was not significant (see Appendix C), thus meeting the assumption of linearity (Field, 2018). However, the interaction term for cumulative credit hours earned was significant ($p = 0.039$). The second model, semester one to semester three, proved the opposite to be true. The interaction term for cumulative grade point average was significant ($p = 0.014$), thus violating the assumption of linearity (Field, 2018). Whereas, the interaction term for cumulative credit hours earned was not significant (see Appendix C). Hasan (2020) states that a significant interaction should not cause worry if the sample size is large.

Table 3.1

Description of Retention for Dependent Variable Labels

Dependent Variable Label	Description (Control)	Description (Treatment)
Retention Semester 1 to Semester 2 (Retained = 1)	Students completed coursework (date grades posted) in Fall 2018 and enrolled in coursework (census date) Spring 2019, or completed a degree or certificate in Fall 2018, or transferred to another two- or four-year institution January 1—July 31, 2019	Students completed coursework (date grades posted) in Fall 2020 and enrolled in coursework (census date) Spring 2021, or completed a degree or certificate in Fall 2020, or transferred to another two- or four-year institution January 1—July 31, 2021
Retention Semester 1 to Semester 3 (Retained = 1)	Students completed coursework (date grades posted) in Fall 2018 and enrolled in coursework (census date) Fall 2019, or completed a degree or certificate in Spring/Summer 2019, or transferred to another two- or four-year institution August 1—August 31, 2019	Students completed coursework (date grades posted) in Fall 2020 and enrolled in coursework (census date) Fall 2021, or completed a degree or certificate in Spring/Summer 2021, or transferred to another two- or four-year institution August 1—August 31, 2021

The data cleaning process consisted of filtering, sorting, and manipulating the data in Microsoft Excel and Microsoft Access to ensure an accurate and complete dataset could be entered into SPSS (*v.*28) for analysis. I separated retention into two variables (retained semester one to semester two, retained semester one to semester three), staying consistent with institutional definitions, to determine the effect of the predictor on retention. For each participant, retention was calculated by a student enrolling in coursework in a subsequent semester, as determined by the census date, completing a degree or certificate, or transferring to another two- or four-year institution (see Table 3.1).

Quantitative Findings

This section presents the results of the binary logistic regression analysis. First, I outlined the descriptive statistics, including frequencies for the categorical predictor variables and the outcome variable. Next, I reported the mean, standard deviation, skewness, and kurtosis to summarize the continuous predictor variables. Lastly, I provided the binary logistic regression results for each hypothesis. The following hypotheses guided the study:

- H_0: There is no relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention for semester one to semester two (Y).
- H_1: There is a relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention from semester one to semester two (Y).
- H_0: There is no relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention from semester one to semester three (Y).
- H_2: There is a relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention from semester one to semester three (Y).

These hypotheses postulated results of the analyses as based on previous research regarding retention as well as testing the treatment of the population.

Descriptive Statistics

I used descriptive statistics to create a summary profile of the dependent and predictor variables of the participants. Before administering the binary logistic regression analysis, I used the frequency feature in SPSS (*v*.28) to create the summary profile. Table 3.2 presents the frequency of each categorical variable for both groups, semester one to semester two and semester one to semester three. The dependent variable, retention, yielded 79% (n = 829) retained from semester one to semester two and 57% (n = 597) retained from semester one to semester three. The study included 44% (n = 465) of the participants who received differentiated coaching (treatment), while 56% (n = 585) did not receive differentiated coaching (control). The predictor variable, enrollment status, returned 36% (n = 381) of students were enrolled full-time at the conclusion of the semester once grades posted. The frequency of enrollment status and cohort group remained constant for both groups, semester one to semester two and semester one to semester three. This was because each participant is unique to either the control or treatment group, and their status was recorded at a specific point in time.

Table 3.2

Descriptive Statistics for Categorical Variables (N = 1050)

Categorical Variables	Students Semester 1 to Semester 2		Students Semester 1 to Semester 3	
	n	%	*n*	%
Retention				
Not Retained	221	21	453	43
Retained	829	79	597	57
Enrollment Status				
Part-Time (< 12 credit hours)	669	64	669	64
Full-Time (≥ 12 credit hours)	381	36	381	36
Group				
Control	585	56	585	56
Treatment	465	44	465	44

For the continuous variables, I used the explore feature in SPSS (*v*.28) to create the summary profile (see Table 3.3). Table 3.3 presents descriptive statistics for each continuous variable for students in the two cohorts (control, treatment). Control group participant means and standard deviations were calculated for cumulative grade point average (M = 2.83, SD = 0.65) and cumulative credit hours earned (M = 52.38, SD = 22.69). Additionally, cumulative grade point average exhibited a skewness of -0.90 and kurtosis of 2.65. Cumulative credit hours earned had a skewness of 2.47 and a kurtosis of 9.18. Treatment group participant means and standard deviations were calculated for cumulative grade point average (M = 2.87, SD = 0.74) and cumulative credit hours earned (M = 50.79, SD = 21.25). Additionally, cumulative grade point average exhibited a skewness of -1.36 and kurtosis of 3.58. Cumulative credit hours earned had a skewness of 2.25 and a kurtosis of 6.55. The mean, standard deviation, skewness, and kurtosis remained constant for participants in both groups, semester one to semester two and semester one to semester three. This was because each participant is unique to either the control or treatment group, and their status was recorded at a specific point in time.

Table 3.3

Descriptive Statistics for Continuous Variables (Control N=585, Treatment N=465)

Continuous Variables	M	SD	Skewness	Kurtosis
Control Group Cumulative Grade Point Average	2.83	.65	-.901	2.65
Cumulative Credit Hours Earned	52.38	22.69	2.47	9.18
Treatment Group Cumulative Grade Point Average	2.87	.74	-1.36	3.58
Cumulative Credit Hours Earned	50.79	21.25	2.25	6.55

The explore feature also provided histograms (see Figure 3.3 and 3.4) and boxplots (see Figure 3.5 and 3.6). Figures 3.3 and 3.4 display the mean and standard deviation for the control and treatment group cumulative grade point average at the conclusion of the semester once grades posted, while the latter exhibits a clearer picture of the outliers (n = 8, n = 14) included in the dataset (Figures 3.5 and 3.6). I checked and verified the participant data were correct, noting a grade point average of zero for a sophomore level student is possible if they previously earned credit at another institution. This was because Chaparral Community College does not apply a grade point average based on the performance at a previous institution. A transfer student begins with a grade point average of zero. If the same student withdraws from all classes, their grade point average will remain at zero.

The histograms (see Figure 3.7 and 3.8) and boxplots (see Figure 3.9 and 3.10) include the mean and standard deviation for the independent variable, cumulative credit hours earned at the conclusion of the semester once grades posted. Again, the boxplots provided a more accurate view of the outliers (n = 30, n = 27) in Figures 3.9 and 3.10. I identified the extreme outliers and then checked and verified the participant data were correct. The value of earned credit hours was not entered in error. It is possible for students to accumulate credit hours, for a variety of reasons. They may change paths multiple times, or they might transfer to Chaparral Community College after earning credits at other institutions.

To elaborate on the outliers for cumulative credit hours earned, a few scenarios provide context for why these might occur and skew the data. An example is a military student who attended multiple institutions prior to transferring and earned military elective credits. This student begins general coursework then changes to pursue becoming a nurse, thus accumulating several credits. A second example is a student earning a degree elsewhere and transferring to Chaparral Community College to pursue an alternate career path.

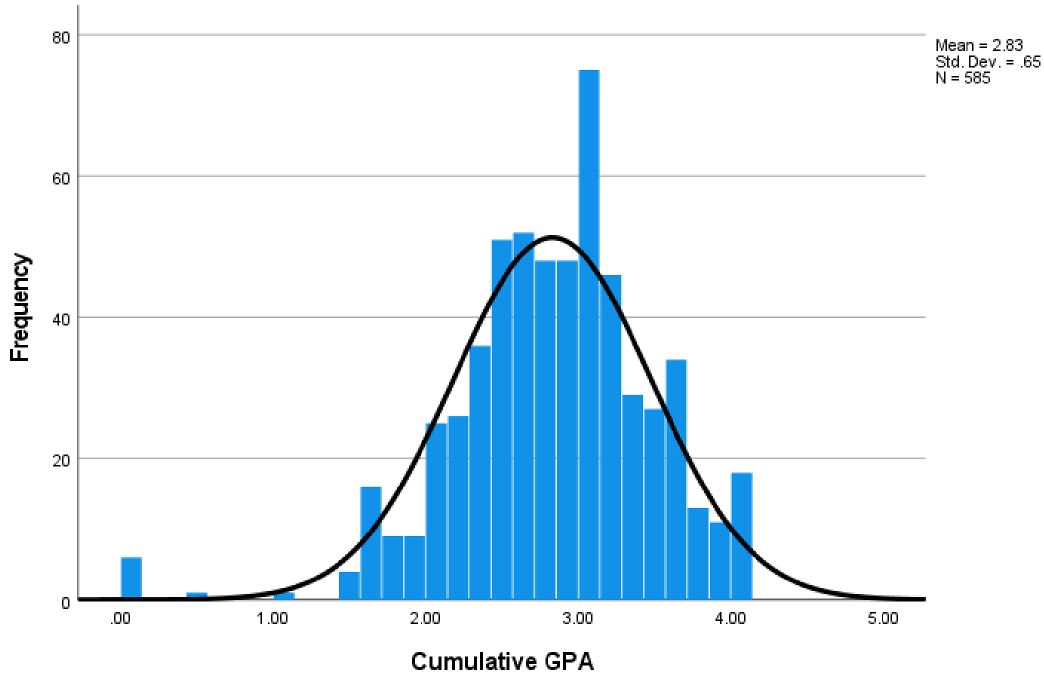


Figure 3.3. Histogram for the control group predictor variable cumulative grade point average.

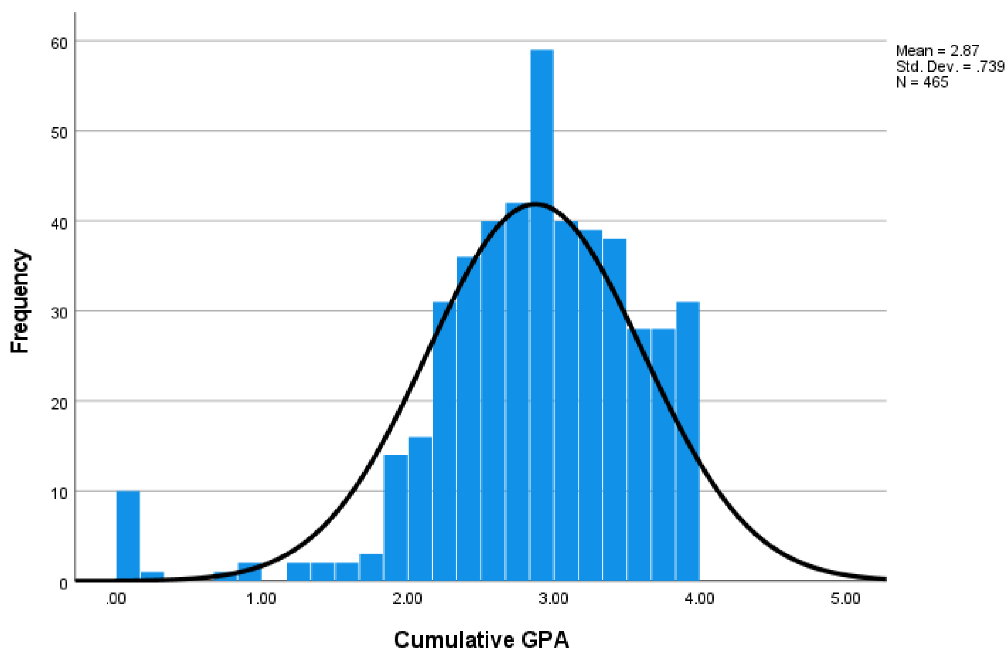


Figure 3.4. Histogram for the treatment group predictor variable cumulative grade point average.

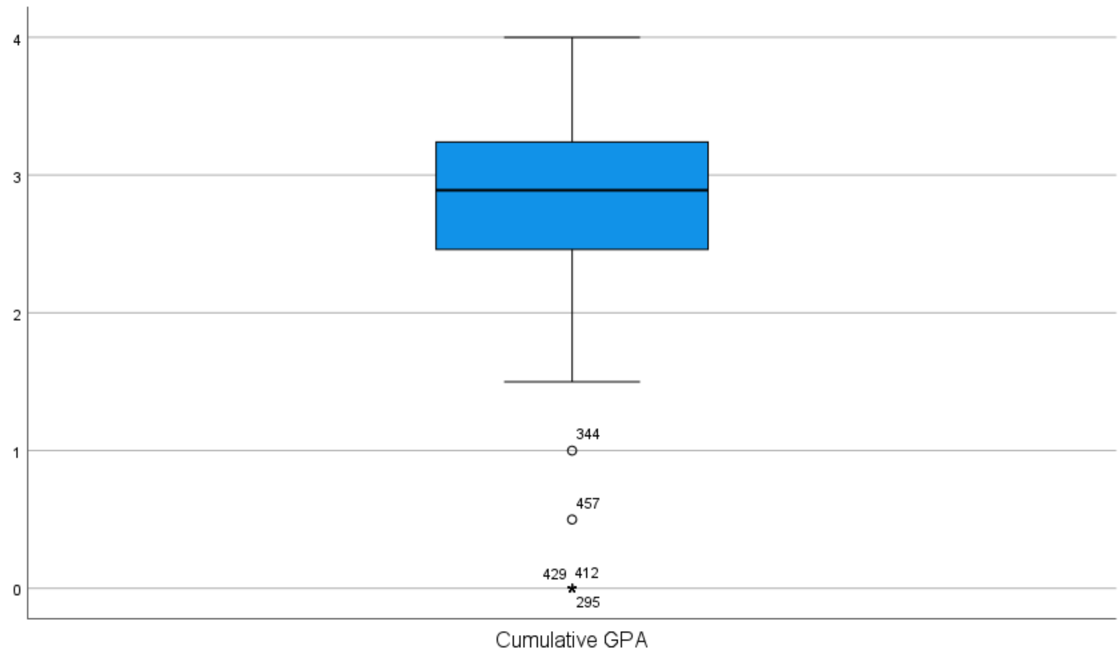


Figure 3.5. Boxplot for the control group predictor variable cumulative grade point average.

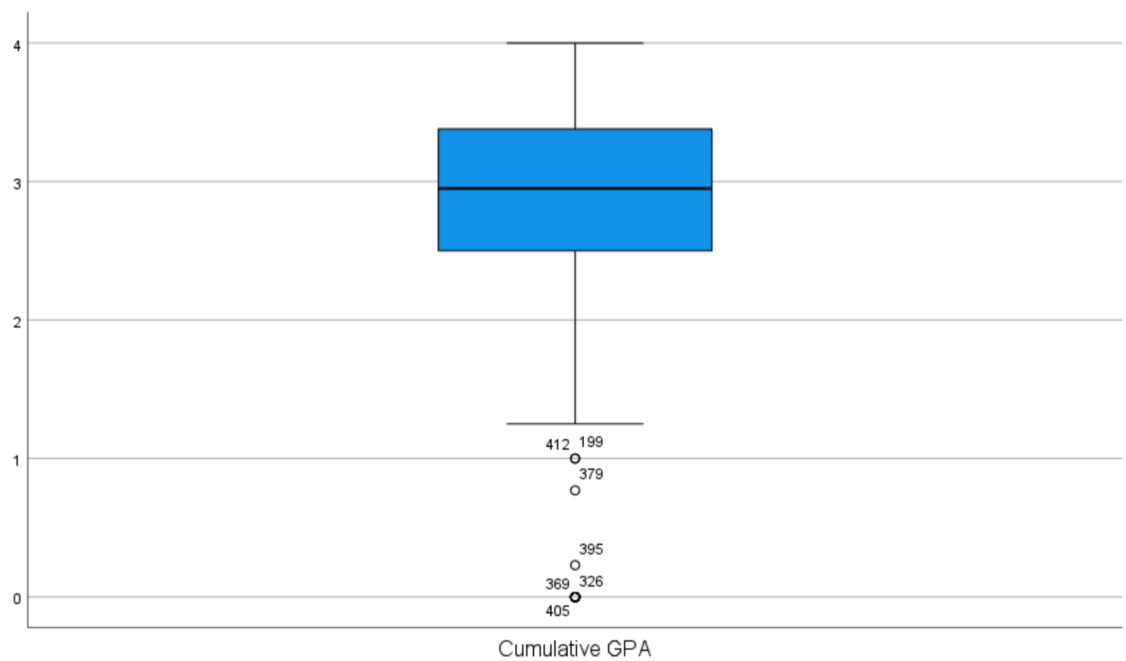


Figure 3.6. Boxplot for the treatment group predictor variable cumulative grade point average.

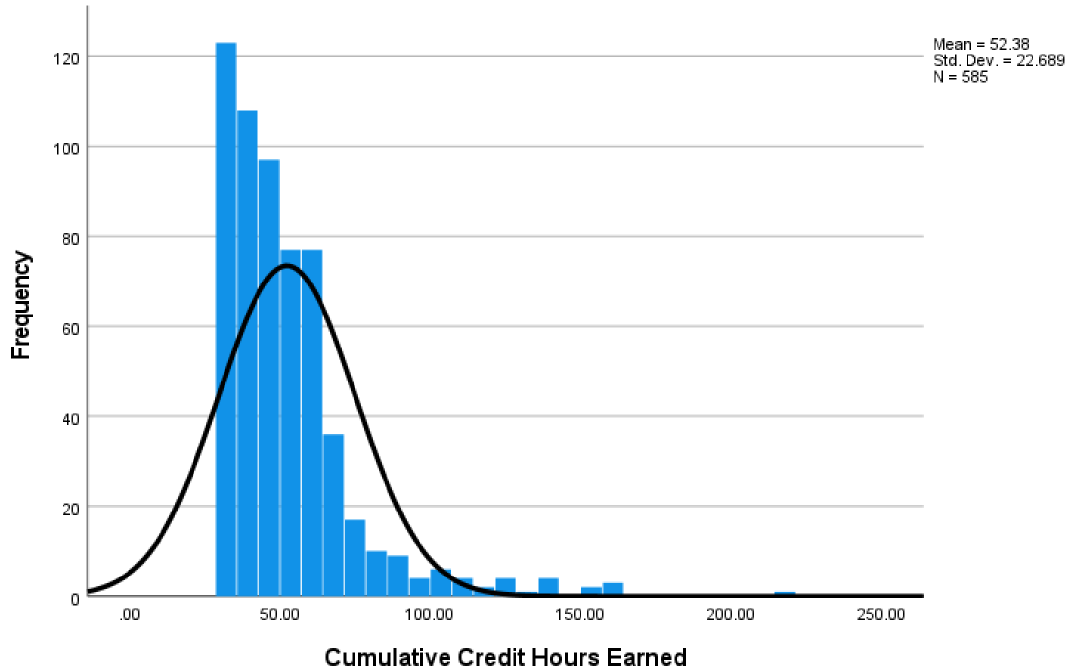


Figure 3.7. Histogram for the control group predictor variable cumulative credit hours earned.

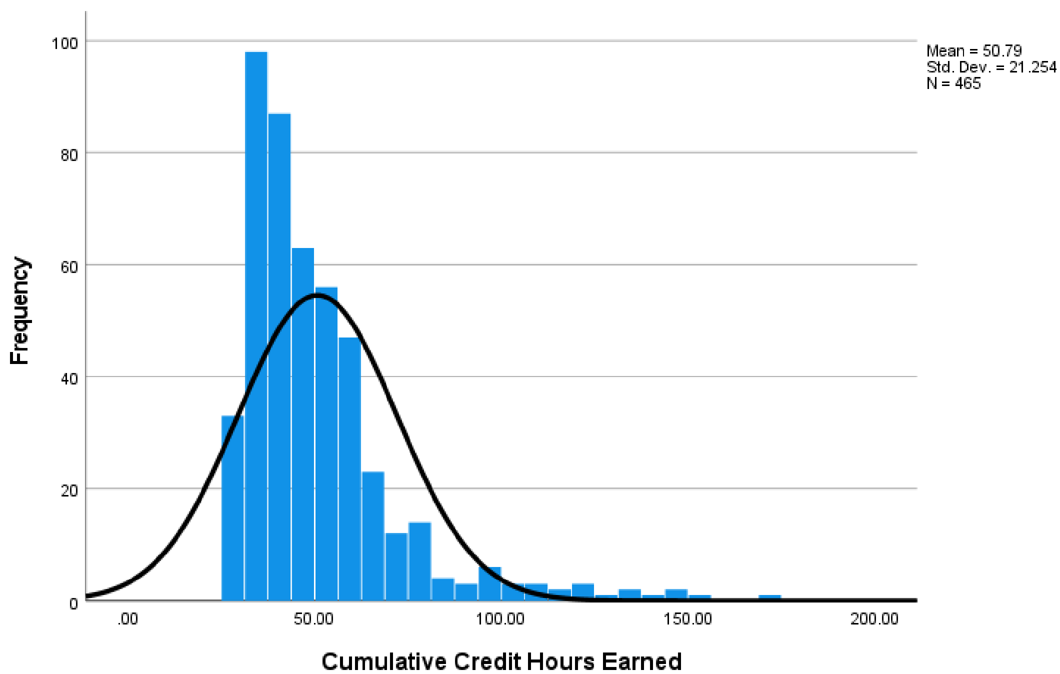


Figure 3.8. Histogram for the treatment group predictor variable cumulative credit hours earned.

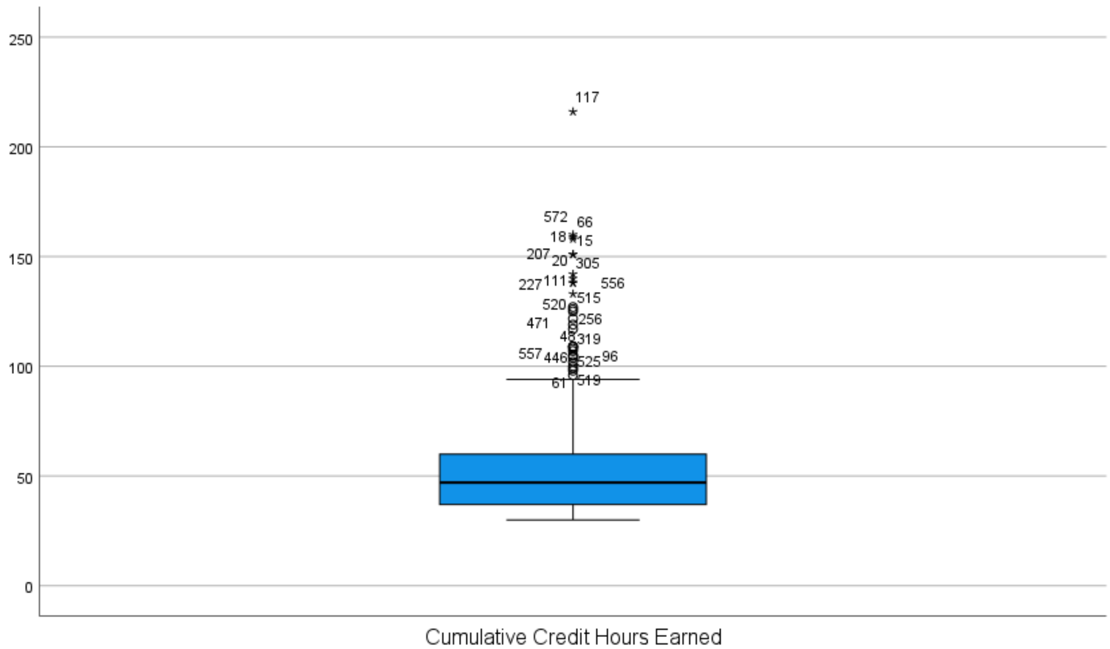


Figure 3.9. Boxplot for the control group predictor variable cumulative credit hours earned.

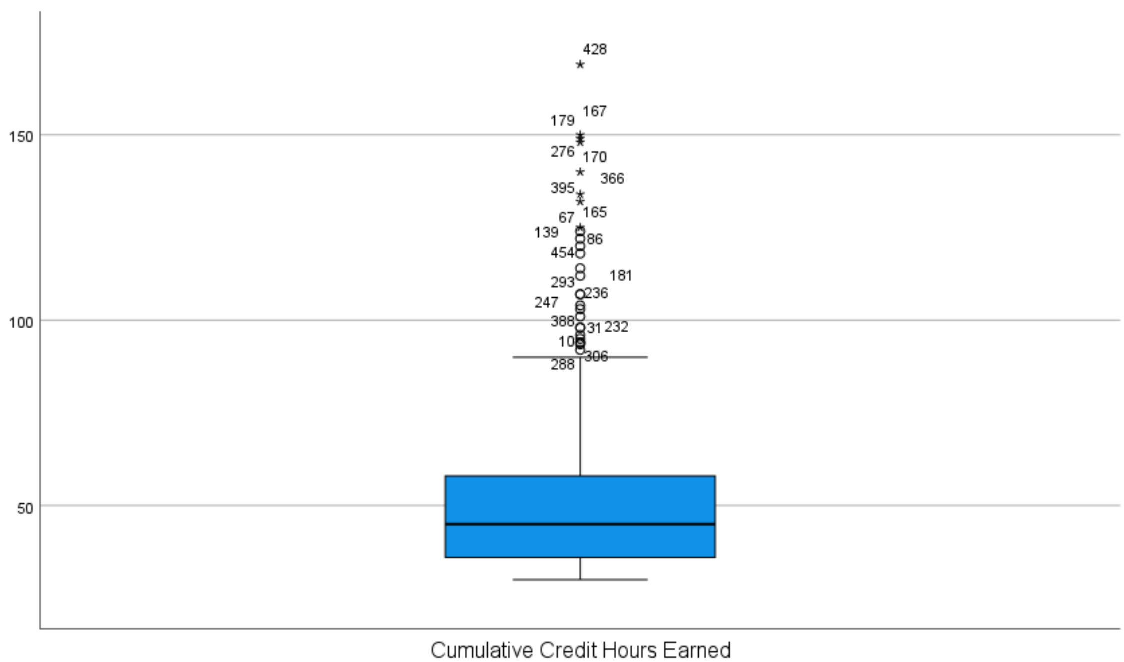


Figure 3.10. Boxplot for the treatment group predictor variable cumulative credit hours earned.

A third example is a student who attempted a program such as licensed vocational nursing, was unsuccessful, and continued to pursue a general associate of science degree. These students have years of educational experience yet choose to begin a new path, and this means they may start from the beginning or build on what they have.

Predictor Variables

I investigated multicollinearity by running collinearity diagnostics using SPSS (*v*. 28). In the first model, the assumption of no multicollinearity was supported (Tolerance = .975 to .995, average VIF = 1.017). No cases had standardized residuals greater than |2.50|, supporting the assumption of no extreme outliers in the model. The assumption of no multicollinearity was supported in the second model (Tolerance = .975 to .995, average VIF = 1.017). No cases had standardized residuals greater than |1.88|, supporting the assumption of no extreme outliers in the model.

Correlation coefficients provided a better understanding of the relationship between the predictor variables and the outcome variables. Two of the variables were categorical, and the descriptive statistics for the continuous variables indicated a violation of the linear model. Therefore, I used Kendall's tau and Spearman's rho to determine the relationship between the predictor and outcome variables (see Table 3.4).

The two continuous variables were analyzed to their relationship to the outcome variable across two points in time. The first continuous variable, cumulative grade point average, showed a significant relationship to both dependent variables (retained semester one to semester two, retained semester one to semester three) as indicated by Kendall's tau $\tau_b = .115$, $p = .001$ and $\tau_b = .151$, $p = .001$. Spearman's rho further confirmed the relationship $r_s = .141$, $p = .001$ and $r_s = .185$, $p = .001$. The second continuous variable, cumulative credit hours earned, also displayed a significant relationship to both dependent variables (retained semester one to semester two, retained semester one to semester three) as evidenced by Kendall's tau $\tau_b = -.075$, $p = .001$ and $\tau_b = -.090$, $p = .001$.

Table 3.4

Correlations Between Predictor Variables and Outcome Variables (N = 1,050)

Test			Retained Semester 1 to Semester 2	Retained Semester 1 to Semester 3
Kendall's tau_b	Group	Correlation Coefficient	.042	.107**
		Sig. (2-tailed)	.177	<.001
	Cumulative Grade Point Average	Correlation Coefficient	.115**	.151**
		Sig. (2-tailed)	<.001	<.001
	Cumulative Credit Hours Earned	Correlation Coefficient	-.075**	-.090**
		Sig. (2-tailed)	.003	<.001
	Enrollment Status	Correlation Coefficient	.181**	.069*
		Sig. (2-tailed)	<.001	.024
Spearman's rho	Group	Correlation Coefficient	.042	.107**
		Sig. (2-tailed)	.177	<.001
	Cumulative Grade Point Average	Correlation Coefficient	.141**	.185**
		Sig. (2-tailed)	<.001	<.001
	Cumulative Credit Hours Earned	Correlation Coefficient	-.091**	-.109**
		Sig. (2-tailed)	.003	<.001
	Enrollment Status	Correlation Coefficient	.181**	.069*
		Sig. (2-tailed)	<.001	.024

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Spearman's rho further confirmed the relationship $r_s = -.091$, $p = .003$ and $r_s = -.109$, $p = .001$. The categorical variable, enrollment status, had a significant relationship to both dependent variables (retained semester one to semester two, retained semester one to semester three) as shown by Kendall's tau $\tau_b = .181$, $p = .001$ and $\tau_b = .069$, $p = .024$. Spearman's rho yielded the same results $r_s = .181$, $p = .001$ and $r_s = .069$, $p = .024$.

Finally, the predictor variable group (control, treatment) did not demonstrate a strong relationship to the dependent variable, retained semester one to semester two, as indicated by Kendall's tau $\tau_b = .042$, $p = .177$ and Spearman's rho $r_s = .042$, $p = .177$. However, there was a statistically significant relationship to the second dependent variable, retained semester one to semester three as evidenced by Kendall's tau $\tau_b = .107$, $p = .001$ and Spearman's rho $r_s = .107$, $p = .001$.

Logistic Regression Analysis

I fit two logistic regression models to the data to address the hypotheses regarding retention. The first binary logistic regression was run to predict the odds of semester one to semester two retention based on participants being in the treatment group. The model also predicted the odds that participants would be retained based on the predictor variables cumulative grade point average, cumulative credit hours earned, and enrollment status. The logistic regression model was statistically significant, $X^2(4) = 76.72$, $p < .001$. The model explained 11.0% (Nagelkerke R^2) of the variance in students retained and correctly classified 79.4% of cases.

The second binary logistic regression was run to analyze the odds that participants would be retained from semester one to semester three based on receiving the treatment. As with the previous model, the odds that participants would be retained based on the predictor variables cumulative grade point average, cumulative credit hours earned, and enrollment status was determined. The logistic regression model was statistically significant, $X^2(4) = 69.47$, $p<.001$. The model explained 8.6% (Nagelkerke R^2) of the variance in students retained and correctly classified 63.5% of cases.

Model 1 hypothesis. To test the hypothesis on the relationship of differentiated coaching to retention, I first reviewed the regression coefficients, odds ratio (OR), and the 95% confidence interval for the OR (see Table 3.5) for the semester one to semester two model. The group independent variable had an odds ratio (OR) greater than the value of 1, indicating a positive relationship with the dependent variable, retained (Crowson, n.d.; Field, 2018). Although the slope for the group was positive, it was not statistically significantly different from 0 ($b = 0.169$, $SE = .160$, $p = .293$), which fails to reject the null hypothesis.

Using the same units of analysis in Table 3.5, I noted for each increase in cumulative grade point average, there was an increased likelihood of being retained. A cumulative grade point average increase of 1.0 is associated with an increase of 85% in the odds of retention at semester two. Students with a higher cumulative grade point average were 1.85 times more likely to be retained than those with a lower cumulative grade point average, thus rejecting the null hypothesis.

Cumulative credit hours earned was a measure of time-to-completion predictor variable, aligning with the pillar of keeping students on the path as included in the Guided Pathways framework (American Association of Community Colleges, 2021; Jenkins, Lahr, et al., 2018). In the first model (see Table 3.5), semester one to semester two, cumulative credit hours earned was a negative and significant predictor of the probability of being retained ($b = -0.010$, $SE = .003$, $p = .003$), rejecting the null hypothesis (Crowson, n.d.; Field, 2018).

The final predictor variable, full-time enrollment status, was a measure of time-to-completion predictor variable which aligned with the Guided Pathways' pillar of keeping students on the path (American Association of Community Colleges, 2021; Jenkins, Lahr, et al., 2018). In the semester one to semester two model (see Table 3.5), students with a full-time enrollment status had 2.53 higher odds to be retained than part-time students. Enrollment status was a positive and significant predictor of the probability of being retained (*b* = 0.928, *SE* = .188, *p* <.001), rejecting the null hypothesis.

Table 3.5

Logistic Regression Model 1 Results Predicting Retention

	Semester 1 to Semester 2 Model					
Variable	b	SE	Wald	p	OR	95% CI of OR
Group (Intervention)	0.169	.160	1.107	.293	1.184	0.865–1.620
Cumulative GPA	0.614	.109	31.660	<.001	1.848	1.492–2.288
Cumulative Credit Hours Earned	-0.010	.003	8.726	.003	.990	0.984–.0997
Enrollment Status	0.928	.188	24.377	<.001	2.530	1.750–3.658

Model 2 hypothesis. In the semester one to semester three model, students in the treatment group who received differentiated coaching were 1.51 times more likely (OR = 1.51) to be retained than those in the control group who did not receive differentiated coaching. Given the 95% confidence interval, the odds of retention could range from 1.17 to 1.95. In this model, the independent variable group was a positive and significant predictor of the probability of being retained (*b* = 0.411, *SE* = .130, *p* = .002), thus rejecting the null hypothesis (Crowson, n.d.; Field, 2018). This finding supports the broader definition of academic integration (Latz, 2015; Tinto, 1993) through a complex perspective of "inclusive-or" (Aoki, 2004; Pratt, 2008a) by helping students stay on their path and ensuring students are learning pillars of the Guided Pathways framework (American Association of Community Colleges, 2021; Jenkins, Lahr, et al., 2018).

In the second model, semester one to semester three, cumulative grade point average was a positive and significant predictor of the probability of being retained (*b* = 0.633, *SE* = .101, $p < .001$), again rejecting the null hypothesis (Crowson, n.d.; Field, 2018). Students were 1.88 times more likely to be retained with a higher cumulative grade point average. Cumulative grade point average was a measure of academic achievement that aligns with academic integration (Tinto, 1993) through the ensure students are learning pillar in the Guided Pathways framework (American Association of Community Colleges, 2021; Jenkins, Lahr, et al., 2018).

In the second model (see Table 3.6), semester one to semester three, the null was again rejected as cumulative credit hours earned was a negative and significant predictor of the probability of being retained (*b* = -0.011, *SE* = .003, $p < .001$; see discussion in Crowson, n.d.; Field, 2018).

Table 3.6

Logistic Regression Model 2 Results Predicting Retention

	Semester 1 to Semester 3 Model					
Variable	b	SE	Wald	p	OR	95% CI of OR
Group (Intervention)	0.411	.130	9.902	.002	1.508	1.167–1.947
Cumulative GPA	0.633	.101	39.282	<.001	1.882	1.545–2.294
Cumulative Credit Hours Earned	-0.011	.003	13.476	<.001	.989	0.983–0.995
Enrollment Status	0.141	.136	1.069	.301	1.151	0.882–1.503

An increase in 1 credit hour earned is associated with a decrease of 11% in the odds of retention at semester three. However, in the second model (see Table 3.6), semester one to semester three, the slope for enrollment status was positive, but it was not statistically significantly different from 0 ($b = 0.141$, $SE = .030$, $p = .301$), thus failing to reject the null hypothesis.

Implications

The purpose of this study was to broaden the definition of academic integration originally proposed in Tinto's (1993) Institutional Departure Model to include experiences beyond the classroom resulting from enrollment in courses (Latz, 2015). By taking a complex perspective, I proposed differentiated coaching as an approach to accomplish academic integration both in and out of the classroom. The framework for analysis was the Guided Pathways model, specifically the two pillars of helping students stay on their path and ensuring students are learning. The three research-based predicting variables aligned with each of the pillars and have been proven to be predictors of retention in past studies (Metz, 2004; Okun et al., 1996; Schwebel et al., 2012; Tinto, 1993). Cumulative grade point average was a measure of academic achievement and therefore aligns with ensuring students are learning. The variables, cumulative credit hours earned and enrollment status, measured time to completion and aligned with keeping students on the path (American Association of Community Colleges, 2021; Jenkins, Lahr, et al., 2018). The findings of this study supported the hypothesis that a differentiated coaching approach deployed through student success programming is a predictor of retention, ultimately leading to degree completion.

Initiatives aimed at retention that involve cross-institutional reform are difficult to evaluate and often take years to observe improvements (Bailey et al., 2015). This study demonstrated the struggle that the treatment, although positively sloped, did not have a statistically significant relationship to retention in the transition from the first semester to the second. However, when students moved along their pathway to the third semester, the differentiated coaching treatment had both a positive and significant relationship to retention. For students who received differentiated coaching, the probability of being retained was increased. This trend is expected to continue as the advisors improve their expertise in differentiated coaching and applying the approach to students' individual experiences.

By rethinking how college administrators approach the pillars of Guided Pathways, integrated as opposed to stand-alone, administrators can reconsider how they approach student success. Differentiated coaching invites an "inclusive-or" conversation, bridging the gap of academic integration by broadening its defined context. When academic integration encompasses efforts both in and out of the classroom, students benefit and exhibit stronger likelihood of retention. In this study, academic support as applied by advisors through the use of tools based on principles of adult learning, motivational interviewing, and holistic advising, directly influences students. The action of intentionally listening to students and allowing them to share their social and academic influences that are occurring simultaneously empowers them to succeed. Success programming designed to deliver solutions with these influences at the forefront moves institutions from transactional to transformative practices. This type of cross-institutional reform involving both student services and instructional services has the greatest potential to positively influence student retention and completion.

Future research in this area may focus on the elements and delivery of differentiated coaching. Student and advisor perspectives would add valuable insight into the effectiveness of the approach. Another component to consider is bringing faculty and student success staff together to design programming and courses which facilitate learning throughout the student experience as they navigate their pathway to a future career. The differentiated coaching approach has the potential to guide these conversations through design thinking and open-mindedness.

Summary and Conclusion

Nationally and locally, community college students complete an associate's degree within three years of enrollment at an alarmingly small rate of 30% or less (Johnstone, 2018; THECB, 2020). As the focus of community colleges shifts from access only to access and completion, retention reform approaches continue to be piloted and implemented with no major impact on the rate of completion. The research indicates that individual reforms cannot stand alone and must not be the responsibility of one department or one office (Bailey et al., 2015). In a time when institutional enrollment has seen a decline only to be magnified by a pandemic (Chaparral Community College, 2019; Chaparral Community College, 2020; Chaparral Community College, 2021), student success administrators must look outside themselves for solutions. Taking a complex perspective, such as using differentiated coaching administered through success programming through a Guided Pathways framework, is an approach that demonstrates much promise for keeping students on the path.

I chose logistic regression analysis as the methodology of this study to determine the relationship between the differentiated coaching approach and semester-to-semester retention rates of sophomore, community college students who were associate degree seeking or general transfer. The predictor variable, cumulative grade point average, proved to be positive and significant predictor of the probably of being retained from semester one to semester two and semester one to semester three. The second predictor, cumulative credit hours earned, was a negative and significant predictor of the probability of being retained regardless of semester. The third predictor variable, enrollment status, showed to be a positive and significant predictor from semester one to semester two but did not have a significant influence to semester three. Finally, the independent variable, differentiated coaching, had a positive slope but was not significant from the first semester to the second. However, by the third semester, differentiated coaching was a positive and significant predictor of the probability of being retained. This probability revealed that cross-college reform has the potential to increase retention rates on a large scale.

Student success administrators, college presidents, and other community college leaders can benefit from these findings if addressing retention reform. Other entities such as the Texas Success Center, the American Association of Community Colleges, and the Community College Research Center may glean best practices from the results of this study. If practitioners make intentional efforts to include stakeholders from across the college to transform practices, colleges can attain significant results.

CHAPTER FOUR

Distribution of Findings

Executive Summary

As enrollment rates continue to decline across the country over 10% since 2019 and 1.7% since 2020 (Texas Association of Community Colleges, 2021; Texas Higher Education Coordinating Board Members, 2021a), it is as important now as it has ever been to be concerned with strategies to keep community college students on their designated path to successful completion. Traditionally, the focus in higher education has been on retaining first-year students. However, Johnstone (2018) reported that nearly one in five students who do not persist at community colleges complete 75% or more of the credit threshold for a degree before leaving the institution. This statistic, combined with the findings of this study, provides evidence that sophomore level students need retention reform as well.

Many community college student success leaders are working to implement Guided Pathways to address stagnant retention rates and low completion rates (Bailey et al., 2015; Jenkins, Brown, et al., 2018). This research study demonstrated that a complex approach to retention reform, viewing the Guided Pathways initiative holistically and not siloed by department, program, or student group, was needed to have a significant enough impact to positively influence student retention (Bailey et al., 2015). The purpose of this quantitative study was to test a Guided Pathways framework to determine the relationship between differentiated coaching, as deployed in student success programming through the Guided Pathways initiative, and retention for associate degree-seeking or general transfer students who have completed at least thirty hours at Chaparral Community College.

Problem Identification

According to Johnstone (2018), approximately 30% of community college students across the United States earn their associate degrees within three years. The Texas Higher Education Coordinating Board Members (THECB, 2020) report 28% of community college students in Texas graduate with an associate degree, bachelor's degree, or certificate within three years. At Chaparral Community College, the percentage is even less, at 24% (THECB, 2020). These statistics demonstrate a need for retention reform that leads to degree completion across colleges regardless of student demographics.

The Texas Success Center, in conjunction with the American Community College Association, promoted the Guided Pathways model to accomplish degree completion benchmarks set by the state of Texas (TACC, 2021; THECB, 2015). The model allows each institution the flexibility to define Guided Pathways to meet the needs of its unique student population. Guided Pathways outlined educational program maps, including specific "course sequences, progress milestones, and program learning outcomes" that aligned to what employers expect of students upon program completion (Jenkins, Lahr, et al., 2018, p. 1). Success experts present Guided Pathways in four pillars: clarify the path, enter the path, stay on the path, and ensure learning (Jenkins, Lahr, et al., 2018).

The Guided Pathways model pillar, referred to as helping students stay on their path, lacks retention research and best practices when considering students with at least 30 credit hours. Although community colleges tend to focus on first-semester experiences

(Pascarella & Terenzini, 1980; Reader, 2018; Schaeper, 2020; Schroeder, 2013), institutions pay little attention to those students "in the middle" or what would be considered the sophomore level. While I have found little evidence at the community college level, a few studies have been completed at the university level regarding this group in the middle (Gump, 2007; Tower et al., 2015; Webb & Cotton, 2019).

Despite research in this area being limited, studies exist that focus on specific programming generally associated with Guided Pathways, specifically advising efforts and the relationship to student retention (Gore, 2006; Martin et al., 2013; Savage et al., 2019; Schwebel et al., 2012; Zhang et al., 2019). These findings reinforced that multiple interventions along a guided academic pathway are necessary to promote student success. However, there remains a need to explore how students engage in these interventions as part of Guided Pathways.

Differentiated Coaching

By adapting the model of differentiated instruction to student success programming, advisors can focus on the student's needs first and then apply the appropriate intervention accordingly. To demonstrate differentiated coaching is a unique approach through a complex lens integrating each component as a network of relations, I created Figure 4.1 to display the interactions between where and how to engage in differentiated coaching. I refer to the bifurcation of these two main ideas as a complex perspective using an "inclusive-or" logic (Aoki, 2004; Pratt, 2008a) applied through differentiated coaching grounded in the two pillars of the Guided Pathway framework.

First, I selected an image of the Lorenz attractor (Quinn, 2013). Lorenz (1995) developed a three-dimensional representation for chaotic flow in a dynamical system.

This representation is a depiction of the pattern of an iterated function oscillating around two basins of attraction. In the case of differentiated coaching, the two basins are student success programming and theories and principles. Student success programming is where the intervention engagement occurs, and theories and principles detail how the engagement with the student occurs. The oscillation does not occur in a linear, deterministic pattern, but rather jumps back and forth between the two components. This division of two components can be described as a bifurcation, which is not a dichotomy of an either-or but shared possibilities of an inclusive-or (Pratt, 2008a).

Figure 4.1. Differentiated coaching approach.

Note. The image of the Lorenz attractor was screen-grabbed from a gif image that maps a sample trajectory through phase space (Quinn, 2013).

Using the Lorenz attractor as a metaphor, I detailed interrelated facets within each basin of differentiated coaching (see Figure 4.1). For the basin of student success programming, the four locations are academic advising, academic coaching, probation programming, and wellness support. For the basin of theories and principles, the methods of holistic advising, motivational interviewing, and principles of adult learning are applied. Each facet can stand alone; however, when treated as separate entities, they cannot move a student toward academic integration at a desirable rate. Separately, these entities become siloed efforts with a narrow focus and limited reach. Differentiated coaching brings the seven together by keeping the student as the central focus.

Data Collection and Analysis

I conducted a quantitative study to determine the relationship between the dependent variable, student retention, and the independent variables, differentiated coaching (group), cumulative grade point average, cumulative credit hours earned, and enrollment status. To effectively address the research question and hypotheses, I determined the population would consist of students that met three criteria: classified as associate degree seeking or general transfer, non-dual credit, and completed a minimum of 30 cumulative credit hours. Associate degree seeking students plan to complete an Associate of Arts, Associate of Science, or Associate of Arts in Teaching degree. I defined “general transfer” as those students who intend to transfer to a four-year institution of higher education.

I sampled two groups to create a control “pre-treatment” group and a “post-treatment” group. First, I selected the control group to include Chaparral Community College students who enrolled in and completed coursework in the Fall 2018 semester and met the three criteria above. Then I identified the treatment group as Chaparral Community College students who enrolled in and completed coursework in the Fall 2020 semester and met the three criteria above. This process resulted in a total of 1,050 participants (585 control, 465 treatment).

Due to the structure of the dependent variable, I used binary logistic regression models to predict membership of only two categories, retained or not retained (Chatterjee et al., 2018; Field, 2018). The log-likelihood statistic was applied to assess the fit or statistical significance of the model. Two logistic regression models were run, semester one to semester two and semester one to semester three. The following hypotheses guided the study:

- H_0: There is no relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention for semester one to semester two (Y).
- H_1: There is a relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention from semester one to semester two (Y).
- H_0: There is no relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention from semester one to semester three (Y).
- H_2: There is a relationship between differentiated coaching, cumulative grade point average, cumulative credit hours earned, and enrollment status and predicted log odds of student retention from semester one to semester three (Y).

These hypotheses postulated results of the analyses as based on previous research regarding retention as well as testing the treatment of the population.

Summary of Key Findings

I fit two logistic regression models to the data to address the hypotheses regarding retention. The first binary logistic regression was run to predict the odds of semester one to semester two retention based on participants being in the treatment group. The model also predicted the odds that participants would be retained based on the predictor variables cumulative grade point average, cumulative credit hours earned, and enrollment status. The second binary logistic regression was run to analyze the odds that participants would be retained from semester one to semester three based on receiving the treatment. As with the previous model, the odds that participants would be retained based on the predictor variables cumulative grade point average, cumulative credit hours earned, and enrollment status was determined. Both models were statistically significant, $X^2(4) = 76.72$, $p<.001$ and $X^2(4) = 69.47$, $p<.001$ explaining 11.0% and 8.6% (Nagelkerke R^2) of the variance in students retained. They correctly classified 79.4% and 63.5% of cases, respectively.

Two Guided Pathways pillars, helping students stay on their path and ensure students are learning, were used as a framework for analysis. The independent variable group (control, treatment) represented the use of differentiated coaching and aligned with both pillars expanding the definition of academic integration. In the first model, the slope was positive, but was not statistically significantly different from 0 ($b = 0.169$, $SE = .160$, $p = .293$), which accepts the null hypothesis (see Table 3.5). Conversely, in the second model, students in the treatment group receiving differentiated coaching were 1.51 times more likely to be retained than those in the control group who did not receive differentiated coaching. The independent variable, group, was a positive and significant predictor of the probability of being retained ($b = 0.411$, $SE = .130$, $p = .002$), thus rejecting the null hypothesis (see Table 3.6; see discussion in Crowson, n.d.; Field, 2018). Initiatives aimed at retention that involve cross-institutional reform are challenging to evaluate and often take years to observe improvements (Bailey et al., 2015). This study demonstrated this struggle as students did not realize a significant effect until they moved along their pathway to the third semester. Here, the differentiated coaching treatment had both a positive and significant relationship to retention. This trend is expected to continue as the advisors continue to develop their expertise in differentiated coaching and the application to students' individual experiences.

Informed Recommendations

The focus of community colleges has shifted from access only to access and completion. Retention reforms have been tested and implemented with no major impact on the rate of completion (Bailey et al., 2015). I offer a proposed solution redefining academic integration (Tinto, 1993) to include academic experiences both in and out of the classroom. Taking a complex perspective that uses "inclusive-or" logic (Aoki, 2004; Pratt, 2008a) and applying it to this new definition allows for extended, holistic support for students to stay on their path and ensure students are learning. A complex lens that integrates these as a network of relations emerges as a unique approach, called differentiated coaching.

The research indicates that individual reforms cannot stand alone and must not be the responsibility of one department or one office (Bailey et al., 2015). In a time when institutional enrollment has seen a decline only to be magnified by a pandemic (Chaparral Community College, 2019; Chaparral Community College, 2020; Chaparral Community College, 2021), student success administrators must look outside themselves for solutions. Taking a complex perspective in which differentiated coaching administered through success programming through a Guided Pathways framework can positively influence student retention.

If addressing retention reform, student success administrators, college presidents, and other community college leaders can benefit from these findings. Other entities such as the Texas Success Center, the American Association of Community Colleges, and the Community College Research Center may glean best practices from the results of this study. If practitioners make intentional efforts to include stakeholders from across the college to transform practices, significant results can be attained.

Findings Distribution Proposal

The findings of this study will prove to be beneficial to many community college leaders focused on retention reform. The following discusses these audiences and explains the need for such research. I propose distribution methods, locations, and materials appropriate for each stakeholder. Finally, I detail my intentions moving forward in presenting this study.

Target Audience

Various audiences will benefit from the contributions this study makes to the discussion on retention reform and the role of Guided Pathways. Chaparral Community College leaders from the President to key personnel in Instructional Services and Student Services will benefit from the outcome indicating that differentiated coaching, as deployed in student success programming through the Guided Pathways initiative, and retention for associate degree-seeking or general transfer students who have completed at least thirty hours have a positive relationship. This study serves as evidence that employing academic integration with an “inclusive-or” complex perspective (Aoki, 2004;

Pratt, 2008a) positively influences student retention, resulting in an increase in completion rates. Further, the Texas Success Center leaders, partners, and community college participants working to advance the Guided Pathways initiative can use the findings as a best practice for implementation. National organizations such as the National Academic Advising Association (NACADA) and the National College Learning Center Association (NCLCA) can use the study to inform the design and development of resources available for institutions looking to reform their student success programming explicitly targeting students with 30 or more credit hours. Finally, educational research groups such as the American Association of Community Colleges and the Community College Research Center should benefit from the data and consider future studies to extend this study beyond sample size, location, and duration limitations.

Proposed Distribution Method and Venue

The proposed distribution of the study results includes multiple forms. I will develop a visual presentation using the Canva graphic design platform to facilitate communicating the results in-person (see Appendix E). This method of demonstrating the results will be presented to the Chaparral Community College Board of Trustees and stakeholders. Presentations will also be made at the next available Texas Success Institute hosted by the Texas Success Center, the national and regional NACADA conferences, and the national NCLCA conference in an effort to further the discussion of retention reform framed in Guided Pathways. To accommodate virtual learners of each organization, I will produce a webinar to provide access to a wide audience of community college constituents. The presentation and webinar will focus on academic integration as outlined by Tinto (1993), the application of differentiated coaching deployed through the Guided Pathways framework, and the relationship to retention of students with 30 or more credit hours.

Distribution Materials

In addition to the institutional and conference presentations, articles will be written and submitted to the *Journal of College Student Retention* and the *NACADA Journal* for publication consideration. These publications are reputable sources for leaders in higher education to reference when researching best practices in retention reform and strategies for student success. Additionally, I will seek to publish with the Texas Success Center as a resource in their Guided Pathways library.

Conclusion

This study showed that differentiated coaching can influence student retention by redefining academic integration to include experiences both in and out of the classroom. By focusing on the two pillars in the Guided Pathways framework, helping students stay on their path and ensure students are learning, advisors bring the academic and social conversation to the forefront. Advisors are better equipped to listen to students and allow them to share their social and academic experiences that are influencing their decisions along their pathway. Complexity theory, academic integration, and differentiated coaching together form a conversation regarding student retention embedded within the Guided Pathways framework (American Association of Community Colleges, 2021; Jenkins, Lahr, et al., 2018).

APPENDICES

APPENDIX A

Institutional Review Board Approval

From: Trevino, Jessica <Jessica_L_Trevino@baylor.edu>
Sent: Monday, June 15, 2020 1:08 PM
To: Lehman, Criquett <Criquett_Lehman1@baylor.edu>; Holland, Deborah <Deborah_L_Holland@baylor.edu>
Subject: Re: IRB Inquiry

Hi Criquett,

My apologies, I accidentally attached the wrong document. Here is the guidance booklet.

Best,
Jessica

From: Trevino, Jessica <Jessica_L_Trevino@baylor.edu>
Sent: Monday, June 15, 2020 12:56 PM
To: Lehman, Criquett <Criquett_Lehman1@baylor.edu>; Holland, Deborah <Deborah_L_Holland@baylor.edu>
Subject: Re: IRB Inquiry

Hello Criquett,

Thanks for answering my question. Based on the information your provided, your study does not qualify as human subjects research because the results would not be generalizable to a broader population because you are focusing on a specific program within a specific community college. Thus, you do not need to submit any documents to our office. Attached is our guidance booklet if you have questions about determinations. Let me know if you have any other questions.

Best regards,
Jessica Trevino

rom: Lehman, Criquett <Criquett_Lehman1@baylor.edu>
Sent: Monday, June 15, 2020 11:19 AM
To: Trevino, Jessica <Jessica_L_Trevino@baylor.edu>
Subject: Re: IRB Inquiry

Jessica,
As of right now my plan is to study students at [redacted] only which means the results will not be generalizable. I am assuming if this changes, I will need to submit another request for review?

Thank you,
Criquett Lehman

From: Trevino, Jessica <Jessica_L_Trevino@baylor.edu>
Sent: Monday, June 15, 2020 11:08 AM
To: Lehman, Criquett <Criquett_Lehman1@baylor.edu>
Subject: Re: IRB Inquiry

Hello Criquett,

Will the results of your study only be specific to [redacted] you are focusing on, or will the results be generalizable to others?

Best regards,
Jessica Trevino

From: Lehman, Criquett <Criquett_Lehman1@baylor.edu>
Sent: Sunday, June 14, 2020 8:07 PM
To: Holland, Deborah <Deborah_L_Holland@baylor.edu>; Trevino, Jessica <Jessica_L_Trevino@baylor.edu>
Subject: IRB Inquiry

Dr. Holland and Ms. Trevino,
Hello, my name is Criquett Lehman and I am currently enrolled in the Learning and Organizational Change EdD online program through the School of Education. I am writing today to inquire whether my Problem of Practice research will qualify as exempt from Institutional Review Board approval.

- My Problem of Practice seeks to determine which elements of guided academic pathways programs have been effective for general transfer students who have competed at least 30 credit hours at a community college. Participants will be currently enrolled community college students who are over the age of 18.
- Purposeful sampling will be used to select participants who meet the criterion of the study. These include students currently enrolled in community college, completed at least 30 semester credit hours, major of record is general transfer (e.g., Associate of Arts, Associate of Science, Associate of Arts in Teaching), and at least 18 years of age.
- Data collection will include internal academic records and interview responses. Internal records will be requested to obtain information such as grade point average, course enrollments, course grades, major of study, student success program participation, retention from semester to semester, and demographics (e.g., gender, ethnicity, full-time/part-time, first generation). The identity of each student record will be concealed. Interview responses will be coded to protect identity and maintain confidentiality. A strict procedure will be followed to ensure anonymity: voluntary participation, informed consent, ability to stop participation at any time, coding of responses, and other interview protocol.

Thank you for taking the time to review my problem of practice. Please let me know if you have any questions regarding my intended area of study and corresponding participants.

Respectfully,
Criquett Lehman

APPENDIX B

Institutional Review Board Site Approval Letter

[redacted]

Date: February 2, 2021

Re: Letter of Cooperation for [redacted]

Dear Baylor University IRB,

This letter confirms that that I, as an authorized representative of [redacted] allow the Baylor University IRB and Criquett Scott access to conduct study related activities at the listed site, as discussed with the Principal Investigator and briefly outlined below, and which may commence when the Principal Investigator provides documentation of IRB approval for the proposed project.

- **Study Title:** A Complex Perspective on Advising: A Quantitative Analysis of Retention Rates for Sophomores who Experience Differentiated Coaching while Attending a Guided Pathways Community College

- **Study Activities Occurring at this Site:** A quantitative analysis will be conducted using student data obtained from the [redacted] student information system. The analysis will include both demographic and academic data, from the student information system to Microsoft Excel via file transfer protocol (FTP). Demographic data consist of age, gender, ethnicity, primary campus location, and enrollment status (i.e., part-time, full-time). Academic data will contain the first term of enrollment, dual credit status, major, semester grade point average, cumulative grade point average, cumulative credit hours earned, number of credits enrolled, and degree completion. Data will be requested for the following semesters at the census date and the date final grades post: Fall 2018, Spring 2019, Fall 2019, Spring 2020, Fall 2020, Spring 2021, Fall 2021, and Spring 2022.

Retention Measures by Cohort

	Cohort 1 (control group)	Cohort 2 (treatment group)
Semester 1 to 2	Fall 2018 to Spring 2019	Fall 2020 to Spring 2021
Semester 1 to 3	Fall 2018 to Fall 2019	Fall 2020 to Fall 2021
Semester 1 to 4	Fall 2018 to Spring 2020	Fall 2020 to Spring 2022

- **Site(s) Support**: Requested support includes the authorization of the Director of Enrollment Management/Registrar to assist in data extraction, provide space and computer to conduct data extraction, and provide access to extracted data files for purposes of outlined research study.

- **Anticipated End Date:** December 2022

[redacted]

I understand that any activities involving compliance with Health Insurance Portability and Accountability Act (HIPAA), Family Educational Rights and Privacy Act (FERPA), or other applicable regulations at this site must be addressed prior to granting permission to the Baylor University researcher to collect or receive data from the site. I am authorized to make this determination on my organization's behalf.

We understand that [redacted] participation will only take place during the study's active IRB approval period. All study related activities must cease if IRB approval expires or is suspended. If we have any concerns related to this project, we will contact the Principal Investigator who can provide the information about the IRB approval. For concerns regarding IRB policy or human subject welfare, we may also contact the Baylor University IRB at irb@baylor.edu.

[redacted] ***February 9, 2021***

[redacted] President, [redacted]

APPENDIX C

Binary Logistic Regression Analysis Testing the Assumption of Linearity

Table C.1

Logistic Regression Model 1 Results for Logit Variables

	Semester 1 to Semester 2 Model					
Variable	b	SE	Wald	p	OR	95% CI of OR
LN_GPA by Cumulative GPA	-1.561	.816	3.655	.056	.210	0.042–1.040
LN_CUM by Cumulative Credit Hours Earned	0.137	.066	4.276	.039	1.146	1.007–1.305

Table C.2

Logistic Regression Model 2 Results for Logit Variables

	Semester 1 to Semester 3 Model					
Variable	b	SE	Wald	p	OR	95% CI of OR
LN_GPA by Cumulative GPA	-2.068	.840	6.064	.014	.126	0.024–0.656
LN_CUM by Cumulative Credit Hours Earned	0.104	.057	3.250	.071	1.109	0.991–1.242

APPENDIX D

Frequency Bar Graphs for Categorical Variables

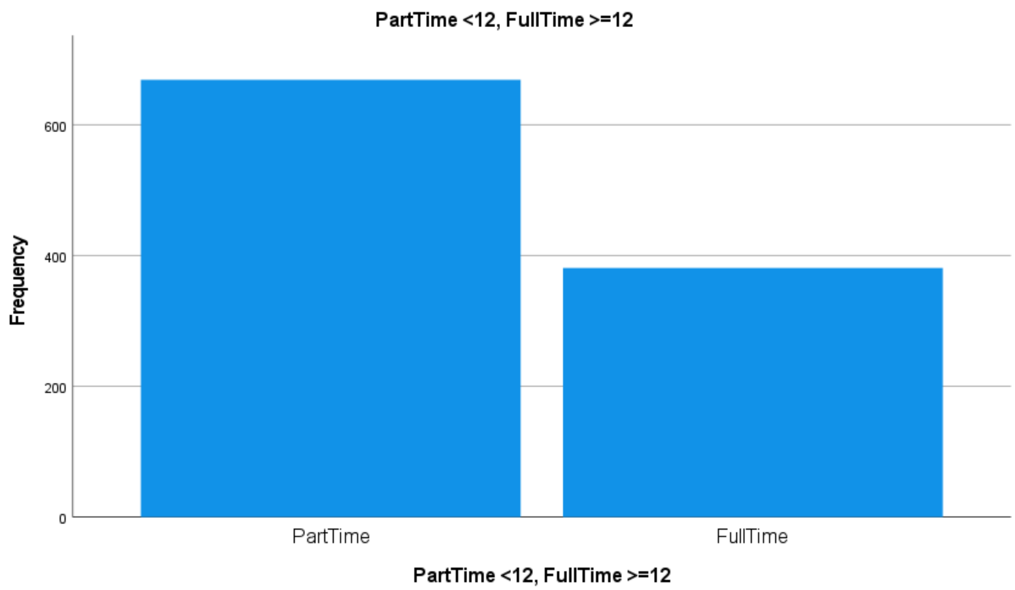


Figure D.1. Bar graph representing frequency for enrollment status.

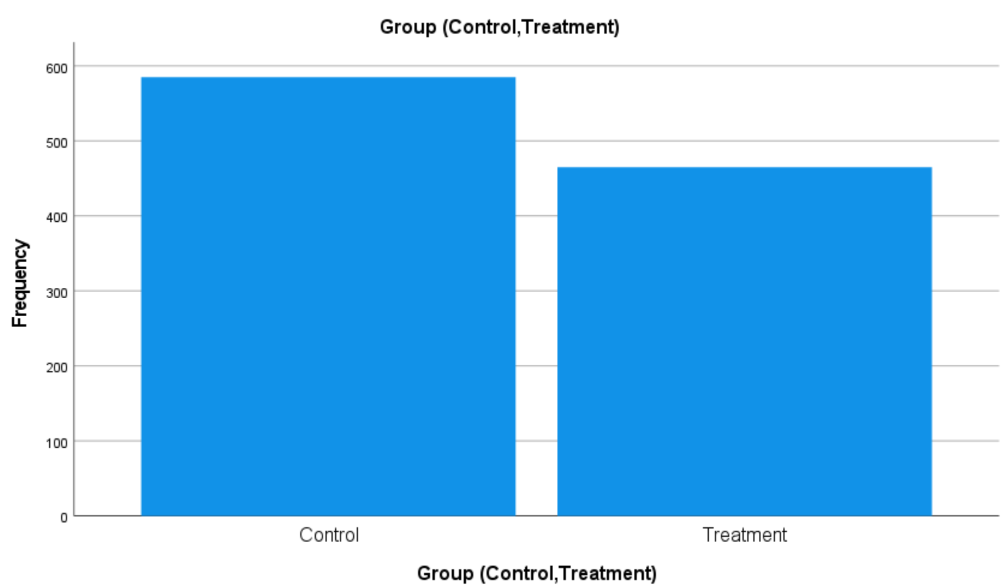


Figure D.2. Bar graph representing frequency for group.

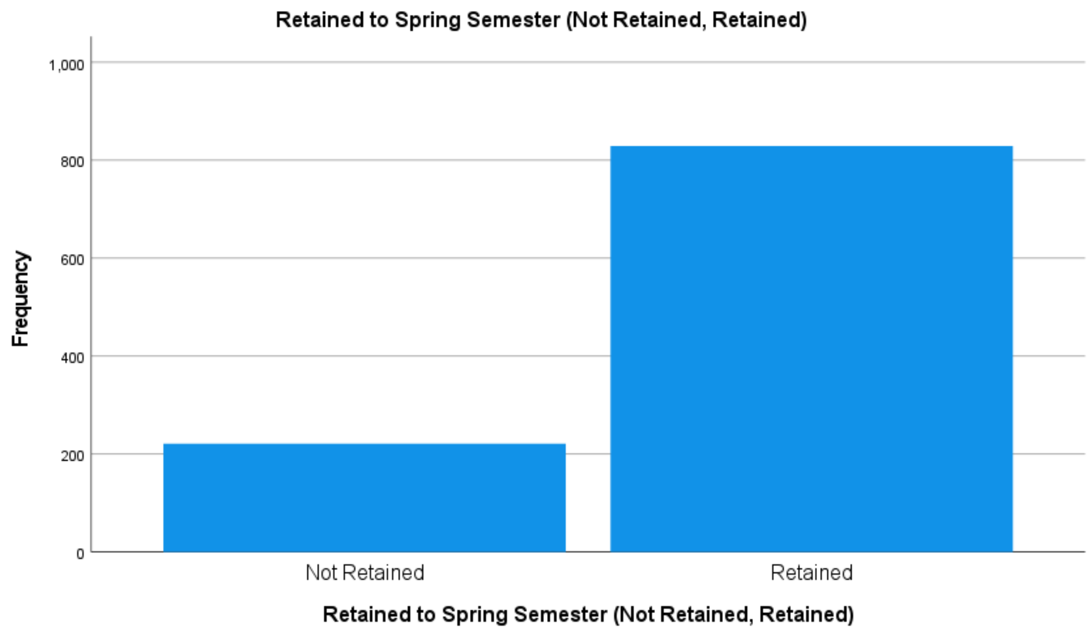


Figure D.3. Bar graph representing frequency for retained to spring semester.

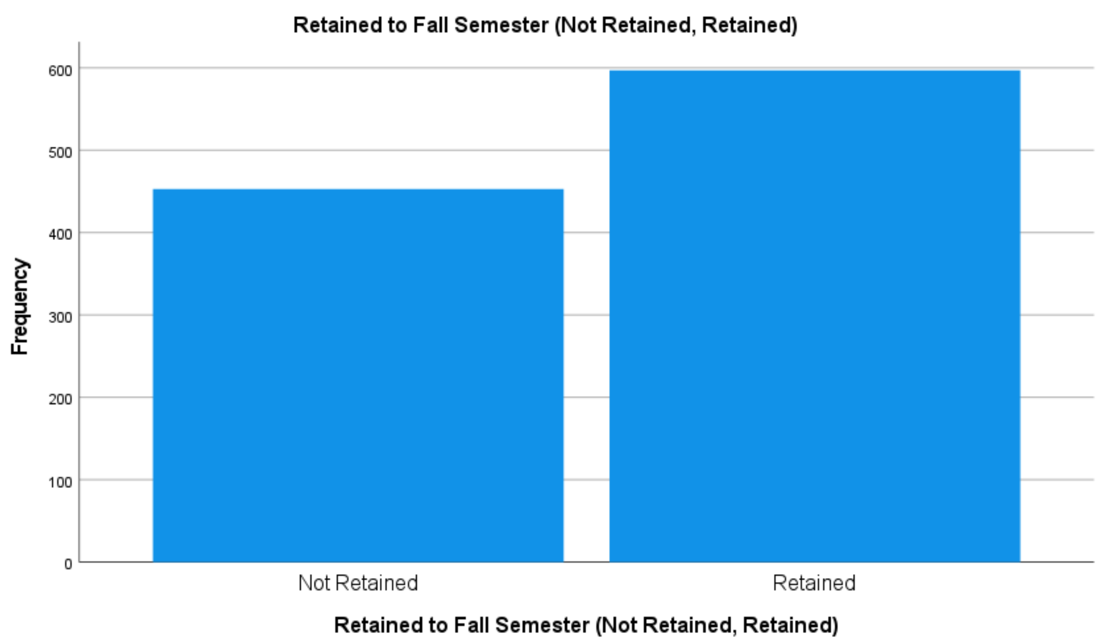
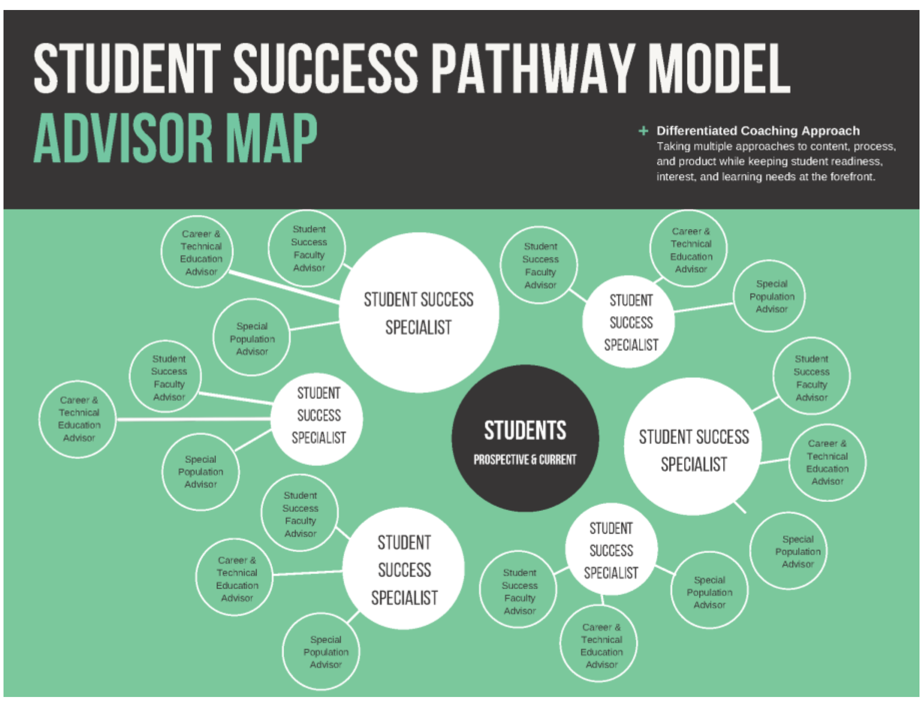
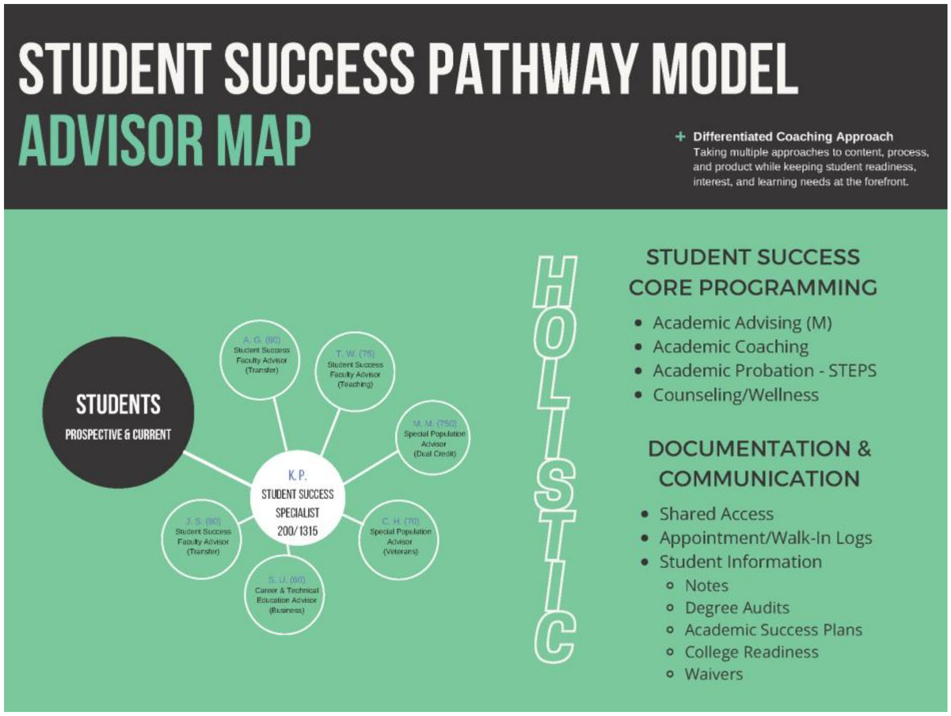


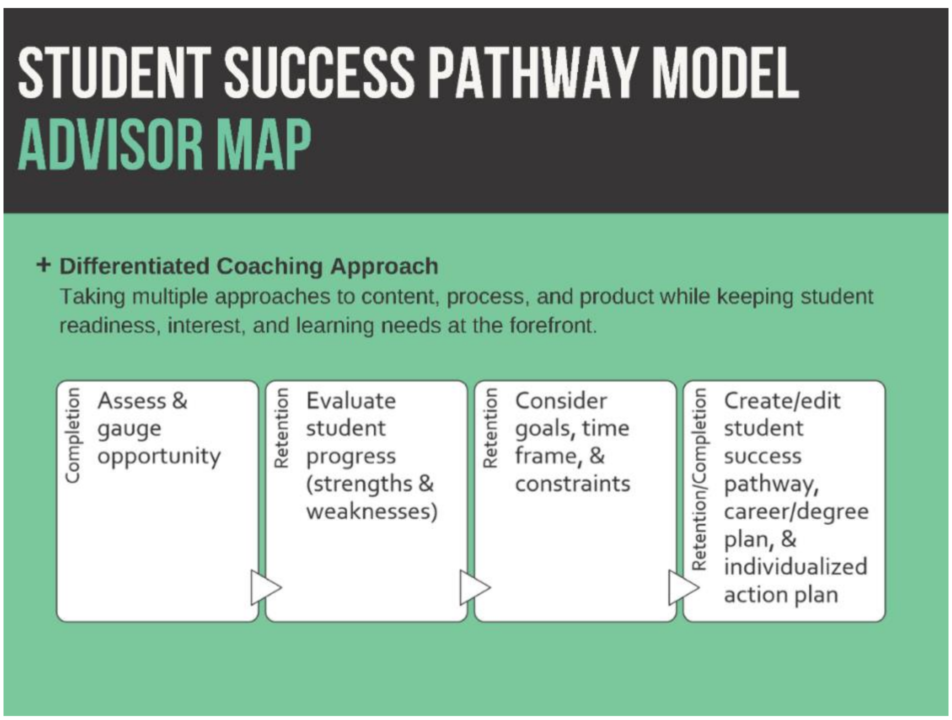
Figure D.4. Bar graph representing frequency for retained to fall semester.

APPENDIX E

Differentiated Coaching Stakeholder Presentation




STUDENT SUCCESS PATHWAY MODEL
ADVISOR MAP
+ Differentiated Coaching Approach
Taking multiple approaches to content, process, and product while keeping student readiness, interest, and learning needs at the forefront.
STUDENTS
PROSPECTIVE & CURRENT
A. G. (80)
Student Success Faculty Advisor (Transfer)
T. W. (75)
Student Success Faculty Advisor (Teaching)
M. M. (750)
Special Population Advisor (Dual Credit)
K.P.
STUDENT SUCCESS SPECIALIST
200/1315
J. S. (80)
Student Success Faculty Advisor (Transfer)
C. H. (70)
Special Population Advisor (Veterans)
S. U. (60)
Career & Technical Education Advisor (Business)
HOLISTIC
STUDENT SUCCESS CORE PROGRAMMING
• Academic Advising (M)
• Academic Coaching
• Academic Probation - STEPS
• Counseling/Wellness
DOCUMENTATION & COMMUNICATION
• Shared Access
• Appointment/Walk-In Logs
• Student Information
  ◦ Notes
  ◦ Degree Audits
  ◦ Academic Success Plans
  ◦ College Readiness
  ◦ Waivers


STUDENT SUCCESS PATHWAY MODEL
ADVISOR MAP
+ Differentiated Coaching Approach
Taking multiple approaches to content, process, and product while keeping student readiness, interest, and learning needs at the forefront.
Completion
Assess & gauge opportunity
Retention
Evaluate student progress (strengths & weaknesses)
Retention
Consider goals, time frame, & constraints
Retention/Completion
Create/edit student success pathway, career/degree plan, & individualized action plan

STUDENT SUCCESS PATHWAY MODEL
ADVISOR MAP

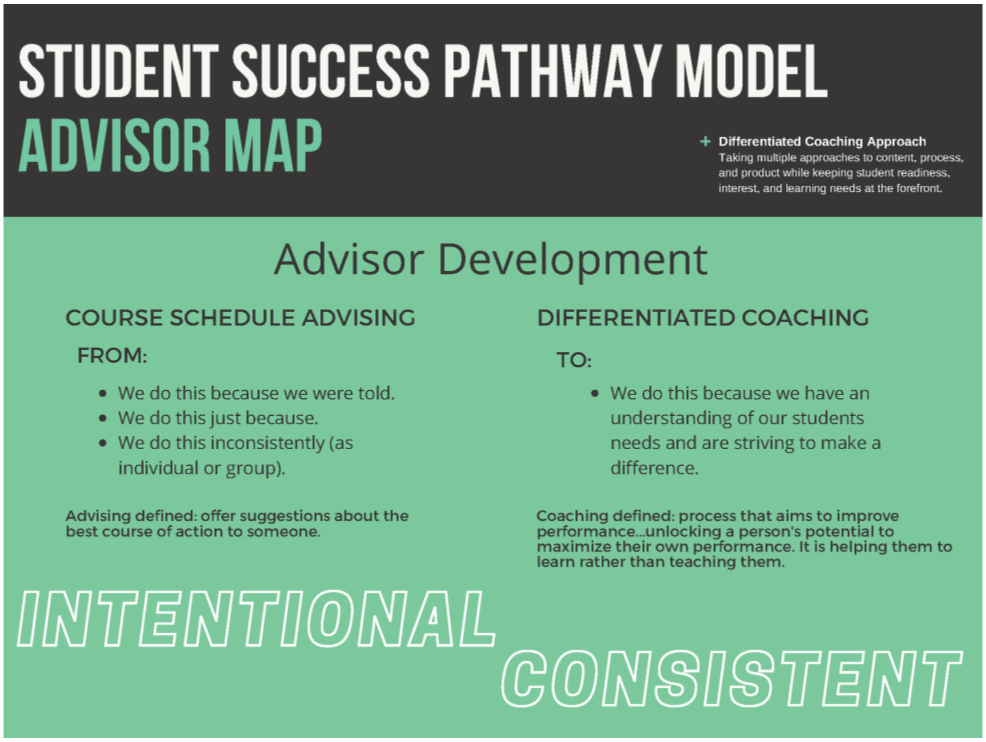
+ Differentiated Coaching Approach

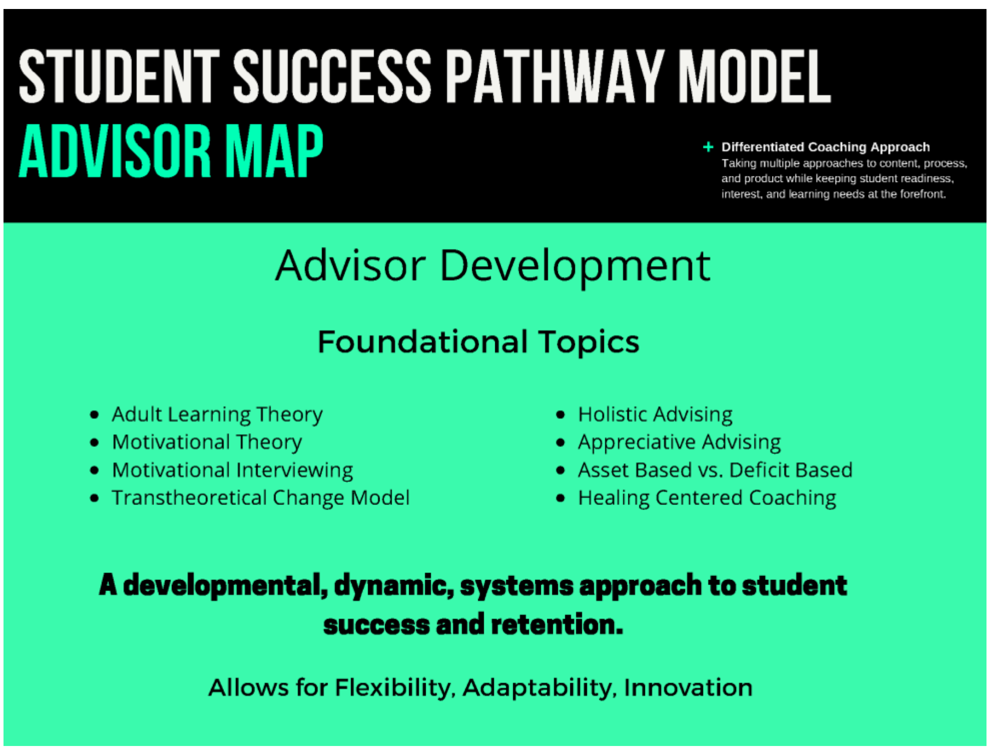
ADVISING ELEMENTS	COURSE SCHEDULE ADVISING	DIFFERENTIATED COACHING
• **Focus**	• Primary: Courses, Secondary: Student Needs	• Primary: Student Needs, Secondary: Courses
• **Student Interviews**	• Ask general information such as major and courses they prefer to take, take note of additional information student volunteers.	• Use motivational interviewing to determine student readiness, interest, and learning needs.
• **Degree Planning**	• Advisors use previous courses to create next semester degree plan.	• Advisors use demographic, academic, and personal factors to create full degree plan.

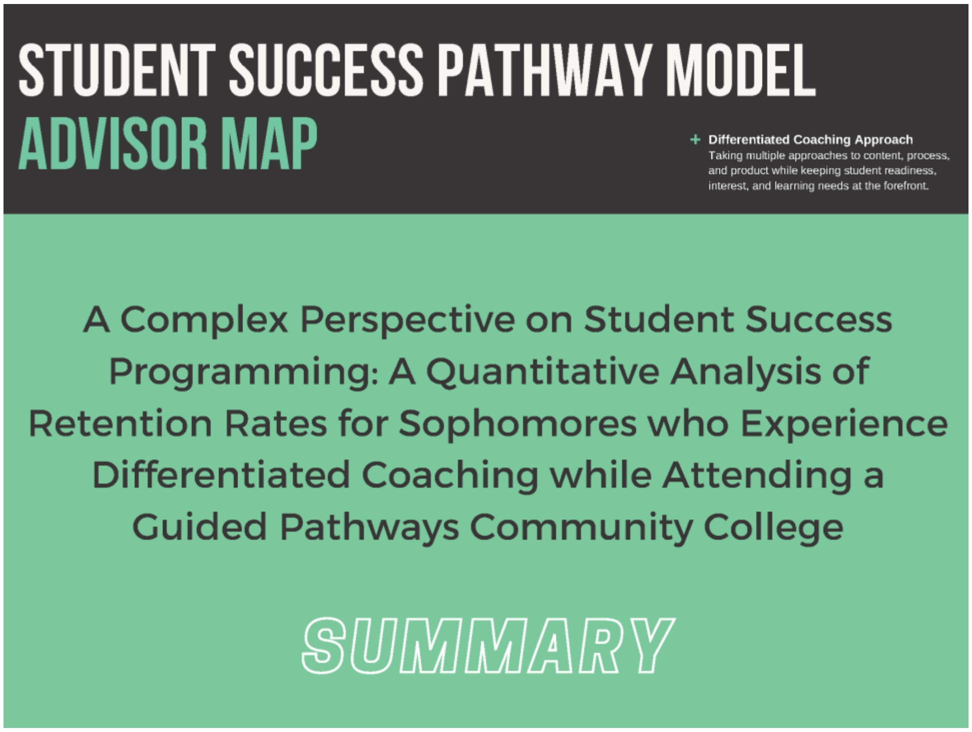
STUDENT SUCCESS PATHWAY MODEL
ADVISOR MAP

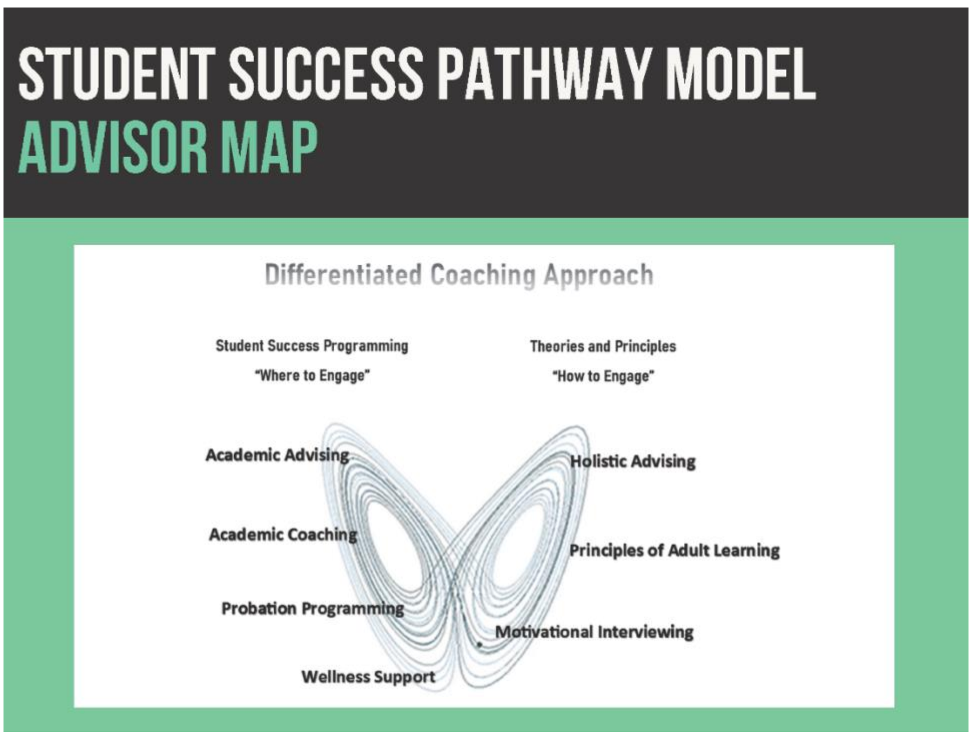
+ Differentiated Coaching Approach

Difficult Cognitive Elements	Why Difficult?	Common Errors	Cues and Strategies Used
Assessing whether the student's assigned student success pathway makes sense, including time to completion	• Advisors tend to focus on basic facts, degree plans only • Students reluctant or not knowing how to share pertinent information; are hesitant to make career/pathway decision	• Don't recognize or investigate for potential barriers • Focus exclusively on information presented by student	• Consider whether you really know all the "layers" of the student story • Use motivational interviewing techniques to get students talking to elicit information beyond that which was initially presented


STUDENT SUCCESS PATHWAY MODEL
ADVISOR MAP
+ Differentiated Coaching Approach
Taking multiple approaches to content, process, and product while keeping student readiness, interest, and learning needs at the forefront.
Advisor Development
COURSE SCHEDULE ADVISING
FROM:
• We do this because we were told.
• We do this just because.
• We do this inconsistently (as individual or group).
Advising defined: offer suggestions about the best course of action to someone.
DIFFERENTIATED COACHING
TO:
• We do this because we have an understanding of our students needs and are striving to make a difference.
Coaching defined: process that aims to improve performance...unlocking a person's potential to maximize their own performance. It is helping them to learn rather than teaching them.
INTENTIONAL
CONSISTENT


STUDENT SUCCESS PATHWAY MODEL
ADVISOR MAP
+ Differentiated Coaching Approach
Taking multiple approaches to content, process, and product while keeping student readiness, interest, and learning needs at the forefront.
Advisor Development
Foundational Topics
• Adult Learning Theory
• Motivational Theory
• Motivational Interviewing
• Transtheoretical Change Model
• Holistic Advising
• Appreciative Advising
• Asset Based vs. Deficit Based
• Healing Centered Coaching
A developmental, dynamic, systems approach to student success and retention.
Allows for Flexibility, Adaptability, Innovation


STUDENT SUCCESS PATHWAY MODEL
ADVISOR MAP
+ Differentiated Coaching Approach
Taking multiple approaches to content, process, and product while keeping student readiness, interest, and learning needs at the forefront.
A Complex Perspective on Student Success Programming: A Quantitative Analysis of Retention Rates for Sophomores who Experience Differentiated Coaching while Attending a Guided Pathways Community College
SUMMARY


STUDENT SUCCESS PATHWAY MODEL
ADVISOR MAP
Differentiated Coaching Approach
Student Success Programming
"Where to Engage"
Theories and Principles
"How to Engage"
Academic Advising
Academic Coaching
Probation Programming
Wellness Support
Holistic Advising
Principles of Adult Learning
Motivational Interviewing

STUDENT SUCCESS PATHWAY MODEL
ADVISOR MAP

+ **Differentiated Coaching Approach**
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Logistic Regression Model Results Predicting Retention

	Semester 1 to Semester 2 Model				Semester 1 to Semester 3 Model			
Variable	b	SE	OR	95% CI of OR	b	SE	OR	95% CI of OR
Group	.169	.160	1.184	.865-1.620	.411	.130	1.508	1.167-1.947
Cumulative GPA	.614	.109	1.848	1.492-2.288	.633	.101	1.882	1.545-2.294
Cumulative Credit Hours Earned	-.010	.003	.990	.984-.997	-.011	.003	.989	.983-.995
Enrollment Status	.928	.188	2.530	1.750-3.658	.141	.136	1.151	.882-1.503

STUDENT SUCCESS PATHWAY MODEL
ADVISOR MAP

+ **Differentiated Coaching Approach**
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"Thank you to my SSA (Student Success Advisor)! When I was down and wanted to withdraw they made sure to support me and lift me up. They told me to fight the good fight and do not give up. Thank you SSA. I am so glad I am taking this journey with you by my side."

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