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An Analysis of the Impact of Early Alert on Community College Student Persistence in Virginia

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AN ANALYSIS OF THE IMPACT OF EARLY ALERT ON

COMMUNITY COLLEGE STUDENT PERSISTENCE IN VIRGINIA

by

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ABSTRACT

AN ANALYSIS OF THE IMPACT OF EARLY ALERT ON
COMMUNITY COLLEGE STUDENT PERSISTENCE IN VIRGINIA

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Student attrition has been a significant challenge facing higher education for decades and is particularly pronounced within community colleges. Specifically, first-time postsecondary students only experienced a 59.3 percent retention rate between Fall 2013 and Fall 2014; at two-year colleges, less than half (46.9 percent) of students were retained during the same period (National Student Clearinghouse, 2015a). As institutional leaders attempt to increase student retention rates, they often invest in early alert systems, which promise to be a key part of a student success solution.

The Virginia Community College System (VCCS) implemented an early alert system in 2013. The purpose of this quantitative study was to examine the relationship between the use of the early alert system and persistence for students taking developmental education courses and students taking college-level courses in the VCCS. All data were existing data provided by the VCCS Office of Institutional Research and Effectiveness. A quasi-experimental, non-randomized research design with matched-control groups was used evaluate impact on student persistence. Data analysis was conducted using multiple binary logistic regressions.

Results indicate that the early alert system, across all flag types, has a substantial and positive impact on developmental mathematics students. Specifically, for every *Academic* or *Attendance* flag raised (up to three flags), developmental mathematics students are nearly 20

times more likely to persist than those that were not flagged in the early alert system; those that received *In Danger of Failing* flags were more than 37 times more likely to persist. Students enrolled in developmental English courses, however, experienced a positive, but much more modest impact. For every *Academic* flag raised (up to three), they were 1.5 times more likely to persist than developmental English students who did not receive a flag. The impact of *Attendance* and *In Danger of Failing* flags were not statistically significant. Lastly, students enrolled in college-level courses experienced a very mild impact, in some instances positive and others negative.

These findings suggest that college leaders and practitioners should focus early alert resources on developmental mathematics students and continue exploration of implementation practices and alternative retention strategies for students enrolled in developmental English and college-level courses. In addition, results indicate the value of an early alert system in a comprehensive retention plan.

For my friend,

ERIKA POINDEXTER,

1979 – 2016.

Your kindness and optimism were my guiding light through this journey.

I will forever be grateful for our friendship.

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CHAPTER 1

INTRODUCTION

Student attrition has been a significant challenge facing higher education for decades (Bailey, Jaggars, & Jenkins, 2015; Braxton, Doyle, Hartley, Hirschy, Jones, & McLendon, 2014; Nodine, Venezia, & Bracco, 2011; Tinto, 1993, 2007, 2012). These challenges are more pronounced within community colleges (Bailey et al., 2015; National Student Clearinghouse [NSC], 2015a). Over time, academicians have produced volumes of research examining the causes of student departure and theorizing how to enhance retention. Likewise, policymakers and practitioners have developed and implemented numerous strategies in hopes of positively moving the needle on retention and completion rates. Despite these efforts, first-time postsecondary students experienced a 59.3 percent retention rate between Fall 2013 and Fall 2014; at two-year colleges, less than half (46.9 percent) of students were retained during the same period (NSC, 2015a).

As institutional leaders continue to try to increase student retention rates, they often invest in early alert systems, which promise to be a key part of a student success solution. Early alert systems, a method used by colleges and universities to identify students demonstrating an at-risk behavior(s) and prompt intervention(s) to prevent attrition (Tampke, 2013), are predicated on the notion that if students at risk of failing or dropping out receive interventions and resources early in the semester, they are more likely to change their trajectory, achieve course success, and re-enroll (Cohen, Brawer, & Kisker, 2013; Tinto, 2012). Although there are a wide array of early alert systems, they all aim to identify and engage students who are demonstrating behaviors indicative of failing coursework or dropping out of college (Barefoot, 2004). This proactive approach relies on college faculty and staff to flag students in need and intervene early in the semester rather than waiting for a student to self-identify and seek assistance (Tinto, 2012).

Limited studies point to the impact of early alert systems in four-year institutions and specific populations within community colleges (i.e., developmental education students), creating a need among community college leaders for more comprehensive, empirical research to determine the retention outcomes and value of continued investment in early alert systems. This study contributes to the understanding of the impact of early alert systems on community college student persistence.

Background

In an era of growing demands for public accountability in higher education, student retention and completion are of paramount importance (Altbach, 2011). Policymakers and college leaders are regularly reminded that the return on a student's educational investment lies in degree attainment (Kuh, 2008; Kuh, Kinzie, Buckley, Bridges, & Hayek, 2006; Nodine et al., 2011; Tinto, 2012). The Pew Research Center (2014) found that wage earnings among millennials without a college degree are 62 percent lower than their counterparts with a college degree. While earning differentials are lower for community college graduates than those with a bachelor's degree, benefits for completing a two-year degree outweigh those of a high school graduate. For instance, graduating from college – four-year and two-year alike – increases the likelihood of degree attainment in subsequent generations (Tinto, 2012). Similarly, the benefits of degree attainment extend beyond financial rewards (Berdahl, Altbach, & Gumport, 2011). College graduates experience better health, greater civic engagement, increased voting rates, lower unemployment, and greater competitiveness in a global market (Rose, 2013). The value of college completion points to the heart of why retention and completion rates in the United States are a matter of importance and urgency.

Community College Context

Two-year colleges were first created in America nearly 100 years ago to provide a venue for publicly funded, accessible postsecondary education open to all who desired it (American Association of Community Colleges [AACC], 2016; Cohen et al., 2013). Now enrolling more than 12 million students annually, community colleges provide an open door to economic prosperity and upward mobility for vulnerable populations (Bailey et al., 2015). This access mission, however, is mirrored with completion rates below 40 percent (Bailey et al., 2015; NSC, 2015a). Thus, understanding the causes of community college student attrition and the practices that promise to enhance retention is imperative to college leaders, policymakers, employers, and taxpayers.

Dual mission. Throughout their history, community colleges have been guided by an access mission that calls them to provide academic and workforce training to all who desire it (AACC, 2016). Low completion rates, however, have caught the eye of governmental policymakers nationwide, who are now demanding greater accountability (Bailey et al., 2015). In 2009, President Obama announced his College Completion Challenge, which calls community colleges to work together to increase "the number of community college students completing a degree or other credential by 50 percent - to five million students by the year 2020, while increasing access and quality" (AACC, 2010, p.1). National organizations, state systems, and institutions nationwide have committed to this achieving this goal. The completion agenda, however, prompted a significant tension between the pre-existing access mission and a new found completion mission (Bailey et al., 2015; Dougherty & Townsend, 2006).

Underrepresented student population. Bailey et al. (2015) state, "The role community colleges play in providing postsecondary access to underrepresented students is obvious when one examines the demographics of their enrollment: they serve a disproportionate number of low-income, immigrant, first-generation, and ethnic minority students" (p.1). Likewise, approximately two-thirds of students enrolled in community colleges arrive academically underprepared for college-level curriculum and require at least one developmental education course (Bailey, 2009; Bailey & Cho, 2010). Of students referred to developmental education coursework, only one quarter will earn a degree or certificate within eight years (Bailey & Cho, 2010). In addition to the challenges associated with academic development, 60 percent of community college students attend part-time (AACC, 2015), which can directly impact social integration, involvement, engagement, and ultimately, likelihood of completion (Braxton et al., 2014; Tinto, 1993). Lastly, 36 percent of community college students are first generation, 17 percent are single parents, 7 percent are non-U.S. citizens, and 12 percent have reported disabilities (AACC, 2015). Each of these community college student populations brings a diverse psychological, sociological, economic, and cultural dimension that influence the probability of completion.

Shifting funding models. As noted previously, community colleges leaders are experiencing demands for unprecedented levels of accountability (Altbach, 2011). These experiences come in a variety of forms, including an increased presence of performance-based funding (American Association of State Colleges and Universities [AASCU], 2014). The AASCU (2014) cited performance-based funding as one of the top ten higher education state policy issues in 2014. In fact, roughly two-thirds of states have implemented or are progressing towards implementation of performance-based funding models that focus a least a portion of state subsidies on student outcomes (Bailey et al., 2015). This shift, along with a new dual mission and the diverse student and faculty populations, present a new and complex political environment for community colleges leaders.

Early Alert Systems

With attrition rates greater than 50 percent (NSC, 2015a), early alert systems are intended to boost student retention and completion rates. Employed by a majority of community colleges (Barefoot, 2004), early alert initiatives are intended to engage students and address their deficiencies early in order to increase their likelihood of success (Tampke, 2013). More specifically, early alert systems attempt to identify signs of student attrition and proactively integrate students into the institution. Tinto (1993) posited, “Wide-ranging contact [with faculty and staff] generally leads to heightened commitment and therefore serves…to enhance the likelihood of persistence” (p.117).

Notably, however, community college leaders are readily investing in early alert systems with limited empirical data demonstrating an impact on student outcomes. Existing research on early alert systems has been largely focused on four-year colleges and universities and has produced mixed results (Brothen, Wambach, & Madyun, 2003; Cai, Lewis, & Higdon, 2015; Hansen, Brothen, & Wambach, 2002; Hudson, 2006; Tampke, 2013). For example, when evaluating the impact of early alert systems in an introductory psychology course, studies found that early alert systems had minimal or no impact on student performance (Brothen et al., 2003; Hansen et al., 2002). Cai et al. (2015), however, concluded that early alert systems prompted students to seek tutoring services, which subsequently improved course performance. Similarly, Hudson (2006) demonstrated positive outcomes for students with excessive absenteeism. Lastly, Tampke (2013) evaluated the efficacy of an early alert system in a large four-year university and found positive preliminary results and noted recommendations for broader implementation.

Meanwhile, studies conducted in a community college setting are very limited and have been focused almost exclusively on developmental education students. For example, a quasi-experimental, historically-controlled study of 20,000 developmental mathematics students showed student pass rates increased by 50 percent following early alert interventions (Wladis, Offenholley, & George, 2014). Due to specific implementation practices at the institution studied, however, generalizability of the Wladis et al. (2014) study results is severely limited. In another study, Simpson (2014) used a mixed-methods study to examine the retention rates of developmental educations students following the use of an early alert system. The quantitative findings were not statistically significant, while the qualitative data suggested the early alert systems were ineffective due to a decentralized process, a lack of communication among faculty, staff, and students, and students' lack of knowledge about support services.

In sum, colleges and universities across the nation have implemented early alert systems to combat dismal student retention rates despite limited empirical evidence of their overall impact. Community college leaders need more comprehensive, empirical research to determine the retention outcomes and value of continued investment in early alert systems.

Purpose Statement and Research Questions

Community colleges across the nation are investing in early alert retention systems with little research to indicate effectiveness. The purpose of this study was to examine the relationship between the use of an early alert system and persistence for students taking developmental education courses and students taking college-level courses in the Virginia Community College System.

This study was guided by the following research questions:

1. What impact does the number of *Academic* flags have on student persistence to the next semester?

    1a. What impact does the number of *Academic* flags raised in a college-level course have on student persistence to the next semester?

    1b. What impact does the number of *Academic* flags raised in a developmental English course have on student persistence to the next semester?

    1c. What impact does the number of *Academic* flags raised in a developmental mathematics course have on student persistence to the next semester?

2. What impact does the number of *Attendance* flags raised have on student persistence to the next semester?

    2a. What impact does the number of *Attendance* flags raised in a college-level course have on student persistence to the next semester?

    2b. What impact does the number of *Attendance* flags raised in a developmental English course have on student persistence to the next semester?

    2c. What impact does the number of *Attendance* flags raised in a developmental mathematics course have on student persistence to the next semester?

3. What impact does the number of *In Danger of Failing* flags raised have on student persistence to the next semester?

    3a. What impact does the number of *In Danger of Failing* flags raised in a college-level course have on student persistence to the next semester?

3b. What impact does the number of *In Danger of Failing* flags raised in a developmental English course have on student persistence to the next semester?

3c. What impact does the number of *In Danger of Failing* flags raised in a developmental mathematics course have on student persistence to the next semester?

4. What impact does the number of flags raised have on developmental education student persistence to the next semester?

4a. What impact does the number of flags raised have on developmental mathematics student persistence to the next semester?

4b. What impact does the number of flags raised have on developmental English student persistence to the next semester?

Professional Significance

Results of this study are of value to practitioners as they attempt to better understand the efficacy in early alert systems in three distinct areas. First, greater insight has been established to determine the impact of early alert interventions on students enrolled in college-level and developmental education courses. Such results allow college administrators to target limited resources to the category or categories of students that experience the greatest impact on persistence.

Second, this study determined, within the population and setting studied, the impact of the different types of flags used within the early alert system. Flags are electronic warnings triggered by a college faculty or staff member and issued to a student signaling at-risk behavior and institutional resources available for assistance. Within this study, flags were categorized into four types – *Academic*, *Attendance*, *In Danger of Failing*, and *General Concern*. With results of this study, institutional leaders now have information necessary to alter the types of flags used within the system. For example, if a particular category of flag has little to no impact on student outcomes and persistence, it may be decided to discontinue use of that flag within the system to focus faculty and staff efforts on flags that produce the greatest results.

Finally, this study used a rigorous approach to examine the impact of early alert systems based on the number of flags raised per student (dosage) and student persistence. The findings are again beneficial to practitioners in identifying and targeting resources to areas most positively influenced by use of the system. If, for example, a developmental mathematics student's likelihood of persistence increases when students are engaged by the early alert system, the institution may more appropriately target limited resources on these students that experience a positive impact.

In sum, greater awareness of the populations and use of the system allow institutional leaders and practitioners to make more informed decisions about if and how they continue to invest limited resources. Further, where continued investment is warranted, this study informs faculty and staff of how to engage in the most effective use of the system.

Overview of Methodology

This study employed a quasi-experimental quantitative research methodology that mimics a true experimental design by using matched control groups. Data were collected from three primary sources, including the Virginia Community College System (VCCS) student information system, the VCCS early alert system as well as the National Student Clearinghouse. The VCCS is a centralized system of 23 community colleges that employ one common student information system and early alert system. The NSC is a national organization that focuses on educational reporting, data exchange, verification, and research services (NSC, 2016). The population examined in this study was a cohort of program-placed VCCS students enrolled in a 16-week course in Fall 2015. This population was selected because it was the most recent cohort for which fall-to-spring persistence could be measured at the time of data analysis, which occurred in Spring 2017. While VCCS colleges offer courses spanning a variety of lengths, a majority of courses are 16-week courses that follow a similar schedule for issuing early alert warnings. Limiting the population to program-placed students prevented examining students who were intentionally enrolled for a short-time and without a long-term academic goal. Similarly, it was assumed that program-placed students desired completion or persistence to the next term.

Data were collected through collaboration with the VCCS Office of Institutional Research and Effectiveness (OIRE). Data from the student information system included student demographics, course enrollments, and completions. Data from the early alert system indicated the details of the flags raised, by student, and course. Lastly, data from the National Student Clearinghouse, collected via the VCCS OIRE, provided information on students who persisted in higher education at an institution outside of the VCCS.

To draw meaningful comparisons between students who had a flag raised and those that did not, matched control groups were created for each research question. The matched control groups were created using the following match factors: Pell-recipient status, full- or part-time status, first generation status, and age. Further, the population identified in the research question – those enrolled in college-level courses and those enrolled in developmental education courses – were mimicked in the matched control group.

Following establishment of the matched control groups, analysis was conducted using multiple binary logistic regression models. Further, a regression model was selected to predict an outcome based on a number of variables. More specifically, logistic regressions were utilized due to the binary outcome of each of the three research questions as there were only two possible outcomes – a student persisted or they did not.

Delimitations

This study was confined to examining the impact of an early alert system on student persistence. It cannot be assumed that the results of this study apply to all forms of early alert systems nor applied to other student populations. Nonetheless, the study does provide evidence of the efficacy of such a system across a large and diverse community college student population. Further, the study examined the impact of the early alert system, and specifically the types of flags raised within the system and the number of flags raised per student, on student persistence for three student populations – those in a college-level courses, those in a developmental mathematics, and those in developmental English.

The population examined in the study was limited to students enrolled in Fall 2015, who were program-placed and were enrolled in at least one 16 week course. Therefore, the results of the study may not be applicable to students who were not yet program-placed nor those that were only enrolled in an abbreviated or open-entry, open-exit (dynamic) courses that have fluid start and end dates. Further, the treatment group within the study consisted of students who had one or more flag(s) raised during the Fall 2015 semester.

Lastly, this study did not evaluate how the early alert system was implemented within the system or individual institutions nor perceptions of the early alert system. Further research is warranted to examine the qualitative components to implementation, utilization, and perceived impact of early alert systems on student persistence.

Definitions of Key Terms

The following key terms were used in this study:

1. College-Level Course – A course that, when successfully passed, results in college-level credit awarded to the student; labeled with a course number of 100 or greater.
2. Community College - A publicly-supported institution regionally accredited to award the associate degree as its highest degree (Cohen et al., 2013).
3. Completion Rate – The percentage of students who have obtained a degree or certificate at any institution within six-years (NSC, 2015b).
4. Developmental Education Course – Coursework designed to provide students with the math and English skills to succeed in college-level coursework; does not result in college-level credit awarded to the student (Bailey & Jaggars, 2016).
5. Early Alert System – A systemic method used by colleges and universities to identify students demonstrating an at-risk behavior(s) and prompt intervention(s) to prevent attrition (Tampke, 2013).
6. First-Generation Status - Students whose indicates that both parent(s)/legal guardian(s) have no more than a high school diploma. If either parent/legal guardian has at least some college, or if the student only lists one parent/legal guardian, the student is not identified as having first-generation status.
7. Flag – Electronic warnings triggered by a college faculty or staff member and issued to a student signaling at-risk behavior and institutional resources available for assistance.
8. Full-time Status - Students enrolled in 12 or more credits in a semester.

9. Part-time Status - Students are enrolled in 11 or less credits in a semester.
10. Pell-Recipient - Students who received a federal Pell Grant. The Pell Grant is a federal, need-based grant that students do not have to repay.
11. Performance-Based Funding – A funding model in which a portion of state funding is linked to quantifiable measures associated with institutional progress in student retention, progression, and completion; designed to incent change in institutional behavior resulting in greater student success (Fingernut & Kazis, 2012).
12. Persistence Rate - The percentage of students who return to college at any institution for their second year (NSC, 2015a).
13. Program-Placed – A student who is pursuing a degree, certificate, diploma, or career studies certificate, as indicated in the VCCS student information system. Student without such an indicator or are dual-enrolled (with the exception of high school students enrolled in a degree or certificate program as identified in Virginia House Bill 1184) are not program-placed.

Summary

Despite decades of research, theories, and institutional strategies, retention remains at the heart of higher education dialogue. In today's political environment, institutional leaders are being pressed to produce unprecedented increases in completion rates while serving an increasingly diverse student body and shifting funding models. As colleges continue to invest in early alert systems as a means to meeting completion goals, this study sought to contribute to the limited body of knowledge about the efficacy of such systems in a community college setting. The following chapter describes further background and key concepts in this study in greater detail.

CHAPTER 2

LITERATURE REVIEW

More than 100 years since its inception, the community college mission to provide access to higher education has been met with challenges in student retention and completion. With public accountability mounting, institutional leaders nationwide have invested in numerous strategies to positively influence completion rates. One such initiative is early alert systems, which claim to identify students at-risk of attrition and position the institution to intervene and change student trajectories toward academic success. Nonetheless, empirical evidence regarding the efficacy of such institutional investments is inconsistent and limited (Bailey & Alfonso, 2005). This study sought to quantitatively examine the efficacy of an early alert system employed across 23 community colleges in Virginia.

This chapter synthesizes relevant literature related to the key constructs of this study, including a theoretical framework, retention in a community college context, early alert systems, and findings of pertinent existing research. The chapter begins with a review of Tinto's Interactionalist Theory of Student Departure, which provides a theoretical framework for early alert systems and the proposed study. Subsequently, literature addressing student retention within the context of community colleges is addressed. Specifically, challenges stemming from a dual mission, diverse and high-need student population, and dependency on adjunct faculty are explored. Lastly, an overview of early alert systems and the research findings related to their efficacy is presented.

Interactionalist Theory of Student Departure

In an attempt to reach the ever elusive goal of student retention, college leaders have relied heavily on research and theory to drive institutional practice. Prior to the 1970s, institutions of higher education largely pointed to student characteristics and psychology to explain attrition (Tinto, 2007). However, seminal research by Tinto (1975) led to development of the Interactionalist Theory of Student Departure, a theoretical framework that describes a shared institutional and student responsibility for retention (Goldrick-Rab & Cook, 2011; Tinto, 1975, 2007). The model revolutionized the paradigm around college student retention by recognizing both the psychological and sociological impacts of the college experience (Tinto, 2007).

Though an array of theories exist, Tinto's (1975, 1993) Interactionalist Theory of Student Departure has reached "paradigmatic status" and is widely referenced in higher education research and practice (Braxton, Hirschy, & McLendon, 2011, p. 2). The theory was revolutionary in that it indicated that student attrition was the result of both individual characteristics and institutional actions (Tinto, 1975, 1993). In addition to an institutional role in retention, the theory also indicates that the lack of student integration in the institution is fundamental. Shortly after Tinto's work was introduced, Pascarella and Terenzini (1980) conducted research that supported the student integration model and added that student engagement with faculty also positively impacts retention. More recently, Barefoot (2005) and Kuh (2008) found a positive correlation between meaningful and purposeful faculty engagement in a student's first year and subsequent retention.

Sociological and longitudinal approach. The Interactionalist Theory of Student Departure (Tinto, 1975; 1993) suggests a longitudinal and sociological view of student departure. Research preceding this theory primarily focused on psychological aspects of student departure, placing responsibility for attrition on student characteristics and personal shortcomings (Tinto, 1993). The Interactionalist Theory of Student Departure, however, focuses on the events that occur between a student and their institution and emphasizes the institutional role in influencing student departure.

While Tinto (1993) acknowledged student characteristics impact retention, he suggested the events occurring post-matriculation carry primary influence on student persistence and completion. More specifically, when describing the theory, Tinto (1993, p. 113) stated,

> Though it accepts as a given the fact that individuals have much to do with their own leaving, it argues that the impact of individual attribute cannot be understood without reference to the social and intellectual context within which individuals find themselves. (p.113)

With more than 775 citations (Braxton et al., 2011), Tinto's theory has proven appealing to college leaders as it suggests institutions may affect retention rates through new and revised practices.

Rites of passage and suicide theories. Drawing on Van Gennep's Theory of Cultural Rites of Passage, Tinto (1993) suggested there are three stages a student navigates when entering and completing college: separation, transition, and incorporation. During the separation stage, a student disassociates with the norms of their previous life and communities. When in the transition stage, as occurs when a student moves from high school to college, the student is in a state of limbo having separated from prior norms, but not yet adapted to their new culture at the college or university. Lastly, a student enters a stage of incorporation by adapting into the postsecondary institution's culture and integrating into college communities and subcultures (Tinto, 1993).

Each stage noted presents unique risks and heightened opportunity for student departure (Tinto, 1993). Though Tinto (1993) was careful not to draw a correlation between a student's progression through these three stages (or lack thereof) and their propensity toward suicide, the author made analogies between voluntary student departure and suicide. Suggesting “a form of educational suicide” (p. 104), Tinto (1993) asserted student departure and suicide share a number of common characteristics, as they both are forms of voluntary withdrawal, serve as a reflection on the community as much as the individual, and signal a “form of rejection of conventional norms regarding the value of persisting in those communities” (p. 99).

Further, Tinto (1993) referenced the “founding father of the discipline of sociology,” Emile Durkheim and his 1970 Theory of Suicide, which sought to explain why different nations experienced varied rates of suicide. Durkheim presented four types of suicide, including altruistic, anomic, fatalistic, and egotistical. The Interactionalist Theory of Student Departure is analogous to the egotistical type, which references an individual’s inability to integrate and establish themselves as a member of a community. Tinto (1993) suggested, within an academic community, social and intellectual integration within faculty and student communities are key to student retention.

Academic and social domains. Within the Interactionalist Theory of Student Departure, Tinto (1993) argued that individuals and institutions are active participants in institutional integration. Such integration can take place in two domains, academic and social. The academic domain represents the formal education of a student. This typically occurs in the classroom or structured extracurricular activities. Conversely, the social domain occurs in the everyday life of the student, including informal interactions outside of the classroom and their personal needs. Tinto (1993) suggested that integration in these two domains, along with individual student disposition, is what drives student persistence. In other words, when integration increases, a student’s commitment to the institution and their goals increase, and the student is more likely to be retained. On the other hand, when a student fails to integrate on these domains, their commitment to the institution and goals wane, as does their likelihood of retention (Tinto, 1993).

Assessment and criticisms. Despite the paradigmatic status of the Interactionalist Theory of Student Departure, it has been the subject of considerable review and criticism. Recently, Braxton et al. (2014), conducted a study to empirically assess the theory's validity and propose revisions in it. The study began by identifying 13 propositions that summarize assertions in the Interactionalist Theory of Student Departure and are open to empirical testing (see Appendix A). The findings led to various revisions, chief among which is the need for two distinct retention theories that reflect the fundamental differences between residential and commuter institutions.

Residential colleges and universities. Although Braxton et al. (2014) asserted that the Interactionalist Theory of Student Departure generally carries explanatory power within residential colleges and universities, they also posit six factors that influence social integration, including ability to pay, commitment of the institution to student welfare, communal potential, institutional integrity, proactive social adjustment, and psychosocial engagement. These six factors translated to eight propositions (noted in Appendix B) that were empirically tested. Ultimately, results showed statistically significant positive results for three of the six of the factors that influence social integration, including psychosocial engagement, commitment of the institution to student welfare, and institutional integrity. They also found social integration at residential colleges and universities "positively influences their degree of subsequent commitment to the institution. The greater the level of the student's subsequent commitment to their institution, the greater their likelihood of persistence to the fall of their second year of college" (Braxton et al., 2014, p. 179).

Commuter colleges and universities. Braxton et al. (2014) also contended Tinto's (1993) theory would need significant modifications to apply to commuter colleges. Unlike residential institutions, the authors suggest the Interactionalist Theory of Student Departure "lacks explanatory power" in commuter colleges and fails to account for the external influences and unique social communities of commuter institutions (p. 109). Thus, Braxton et al.'s (2014) revisions focused on the following three points:

1) student entry characteristics unique to commuter colleges,

2) the vast and influential external environment of commuter students, and

3) the organizational characteristics of commuter institutions.

Mirroring their practice with residential colleges, Braxton et al. (2014) created propositions for empirical treatment. For a complete list of the propositions, refer to Appendix C. Empirical testing indicated four "statistically significant indirect forces in the student persistence in commuter colleges and universities" (p. 121), including academic and intellectual development, commitment of the institution to student welfare, institutional integrity, and support of significant others.

While the work of Braxton et al. (2014) brought attention to a distinction not often addressed in retention theory – the unique characteristics and environment of commuter schools – it did not address two-year colleges specifically. Earlier research conducted by Braxton, Sullivan, and Johnson (1997) found only one of the 13 propositions held validity in two-year institutions. The remaining propositions either received indeterminate results or have not yet been empirically tested. Further research testing the validity of the Interactionalist Theory of Student Departure in community colleges is warranted.

Moving theory to action. Despite more than four decades of research on student retention, institutions still struggle to put theory into action and find meaningful ways to engage students that significantly impact retention rates (Tinto, 2007; 2012). Embracing their theoretical frameworks, Tinto (2012) and Braxton et al. (2011) focus current discussions around moving the student integration framework - or a revision of it - into institutional practice. Attempting to act on theory, institutional leaders are readily investing in early alert systems, but are doing so with little empirical data to demonstrate if the systems are having the intended impact on students' outcomes. Tinto (1993) asserted that a retention program such as early alert systems may be assessed using the following three principles:

1. "Effective retention programs are committed to the students they serve. They put student welfare ahead of other institutional goals;
2. Effective retention programs are first and foremost committed to the education of all students, not just some, of their students;
3. Effective retention programs are committed to the development of supportive social and academic communities in which all students are integrated as competent members" (p. 146-147).

These principles describe a conceptual framework from which institutional leaders may implement and assess the value of an early alert system.

Student Retention in Community Colleges

Despite the development of abundant retention theories in the last four decades and numerous corresponding initiatives, student attrition continues to plague higher education (Bailey et al., 2015; Braxton et al., 2014; Nodine et al., 2011; Tinto, 1993, 2007, 2012). This is evident in national retention rates; less than 60 percent of first-time postsecondary students were retained between Fall 2013 and Fall 2014 (NSC, 2015a). This challenge is even more evident in community colleges that experienced a 46.9 percent retention in the same period (Bailey et al., 2015; NSC, 2015a). Similarly, only four in ten first-time students who enrolled in community colleges earned a two- or four-year credential within six years (NSC, 2015a; Tinto, 2012). There are a number of factors contributing to these challenges and potential solutions addressing student retention in community colleges, which will be explored below.

Evolving mission. America's first community college was established in 1901 in Joliet, Illinois. Since that time, each of the fifty states developed a system of two-year colleges, which have individually and collectively advanced access to postsecondary education and student success (AACC, 2016). Designed to offer a publicly-funded, accessible postsecondary education to Americans previously unable to gain entrée into four-year colleges and universities, community colleges embraced an open-enrollment model and now serve more than 12 million students annually. This represents nearly half (46 percent) of all undergraduate enrollments (AACC, 2016; Bailey et al., 2015; Cohen et al., 2013).

As noted above, while access to higher education has increased, student success (degree attainment) has not kept the same pace. Completion rates below 40 percent (Bailey et al., 2015; NSC, 2015a) have not gone unnoticed by the public and state and national policymakers. As a result, over the last decade, there has been a growing public interest in accountability, thereby expanding the community college mission to also focus on student completion (Altbach, 2011; Bailey et al., 2015; St. John, Daun-Barnett, & Moronski-Chapman, 2013). This new dual mission – access and success - was solidified in 2009, when President Barack Obama introduced the College Completion Challenge, which calls community colleges to increase access and completion rates. Specifically, the Challenge called community colleges to increase "the number of community college students completing a degree or other credential by 50 percent - to five million students by the year 2020, while increasing access and quality" (AACC, 2010, p. 1).

National organizations, such as the American Association of Community Colleges, have followed suit and created initiatives directed at student completion. Likewise, state systems have largely embraced the President's challenge by developing similar statewide goals. In Virginia, for example, the completion agenda is also reflected in the State Council of Higher Education for Virginia's goal to have 1.5 million degrees and workforce credentials awarded by the Commonwealth's public and private colleges by 2030 (State Council for Higher Education in Virginia, 2015). Similarly, the Virginia Community College System adopted a new strategic plan in July 2015 with a singular goal, which states, "Virginia's community colleges will lead the Commonwealth in the education of its people by tripling the number of credentials awarded for economic vitality and individual prosperity" (Virginia Community College System, 2015).

The evolution driving community colleges to a dual mission of access and completion is clear. The call to deliver on both, however, also drives tension perhaps felt most acutely by institutional leaders, who are tasked to serve a student body with unique needs and challenges while increasing the number of students completing degrees and certificates.

Shifting funding models. The completion agenda is reflected in shifting postsecondary funding policies across the nation. Most notably, performance-based funding has been implemented in approximately two-thirds of states (American Association of State Colleges and Universities, 2014; Bailey et al., 2015). While the details of individual performance-based funding models may vary, they are all designed to incent change in institutional behavior by allocating a portion of state funds based on student outcomes (Fingernut & Kazis, 2012). This fundamental shift from enrollment- to performance-based funding intentionally requires college leaders to transfer their attention to student outcomes in order to financially sustain and benefit their institution. Further, the pressure is heightened by the reality that, under most outcomes-based models, lower performance will adversely impact the college by limiting funds needed to effectively serve a high-risk student population. This transformation of fiscal policy fundamentally alters the institutional landscape for which all other policies and practices reside. Some warn that if sustainability of the institution depends on completion, institutional leaders may ultimately consider abandoning the open-access model for a more selective admissions process and improved success rates (St. John et al., 2013).

Community college students. Traditionally open-enrollment colleges, two-year institutions serve students that face unique barriers to student success and completion. Notably, a majority (75 percent) of community college students arrive academically under-prepared (Goldrick-Rab & Cook, 2011). Although not necessarily causal, there is a clear relationship between academic preparedness and completion – as the rate of students needing remediation increases, completion rates decrease (Goldrick-Rab & Cook, 2011). In fact, only one quarter of community college students that require developmental education earn a certificate or degree within eight years (Bailey & Cho, 2010). Thus, if institutional leaders are expected to increase completion rates, delivery of developmental education must be addressed. Some states, including North Carolina and Virginia, have executed a significant redesign of developmental education (Kalamkarian, Raufman, & Edgecombe, 2015). Other states including Florida, Connecticut, and Colorado have altered state policy to substantially reduce the number of students taking remedial coursework (Kalamkarian et al., 2015). Such shifts represent significant institutional amendments of local policies and practices to uphold an open-access model while more efficiently moving students to a level of college readiness and, ultimately, credential completion.

Although community college students demonstrate a greater level of academic deficiencies at entry than those at four-year institutions, Barefoot (2004), asserted that,

> in spite of the predictive nature of poor academic preparation…the majority of drop outs in the United States does not result from academic failure…. The reasons the best students sometime leave may be boredom, lack of academic challenge, poor 'institutional fit', failure to connect to the campus social systems, financial problems, general dissatisfaction or desire to transfer elsewhere. In general, contemporary American college students are not known for their 'product loyalty.' (p. 12)

Thus, it is imperative to examine other qualities of community college students that contribute to retention and the campus environment. Community colleges serve an increasingly diverse population (Garibaldi, 2014; Renn & Reason, 2013), with students who are disproportionately low-income, immigrant, ethnic minorities, single parents, first-generation, and part-time enrolled (Bailey et al., 2015; Goldrick-Rab & Cook, 2011). Further, 36 percent of community college students are first generation, 17 percent are single parents, and 12 percent have reported disabilities (AACC, 2015). While these diverse populations enrich the community college campus and provide diverse psychological, sociological, economic, and cultural dimensions, they also present greater rates of attrition. Further, the characteristics of community college students alter the fashion in which they integrate with the institution, as suggested in Tinto's Interactionalist Theory of Student Departure.

Dependency on adjunct faculty. In addition to a diverse student composition, community colleges demonstrate a high rate of part-time (adjunct) faculty (Altbach, 2011). In

2009, approximately 55 percent of faculty in four-year comprehensive institutions were full-time compared to 31 percent of faculty at two-year colleges (Kezar & Maxey, 2013). Between 1970 and 2001, higher education experienced a 376 percent increase in the number of adjunct faculty, contributing to a diminished sense of academic community and purpose among faculty (Altbach, 2011). After evaluating data derived from the National Survey of Student Engagement and the Faculty Survey of Student Engagement, Kuh (2008) asserts that student engagement is impacted by what faculty value. Thus, if the faculty body feels a lessened connection to the institution and its mission, the growing dependency on adjunct faculty has a direct impact on student learning (Kezar & Maxey, 2013). Reaffirming the importance of the faculty role, Tinto (2007) stated,

> …we know that successful student retention is at its root a reflection of successful student education. That is the job of the faculty. Unfortunately too many of our conversations with faculty are not about student education but about student retention. This must change. We must stop talking to faculty about student retention and focus instead on the ways their actions can enhance student education. If faculty attend to that task, increased student retention will follow of its own accord. (p. 9)

Early Alert Systems

To effectively respond to calls for increased student completion, institutions must move from *knowing why* students do not persist to *implementing actionable plans* that help students succeed (Tinto, 2007; 2012). This need, driven by poor retention rates that result in fiscal challenges for colleges and universities in the form of tuition, state allocations, and potentially performance-based funding, has prompted a thriving “retention industry” that provides a plethora of products and services promising to solve college retention woes (Barefoot, 2004).

Now widely used throughout higher education, early alert systems are one arm of the retention industry and take numerous forms (Barefoot, 2004). Each, however, strives to support academic integration and success by having faculty trigger institutional resources (i.e., intrusive advising or tutoring interventions) when a student performs poorly early in the semester (Barefoot, 2004). By providing early and individualized feedback on a student's challenge(s), there is time for the student to recover learning, performance, and grades. Early alert systems have evolved over the last four decades in terminology and methodology. For example, home-grown systems may be supported by limited levels of technology whereas systems provided by third party vendors rely almost exclusively on a technological interface. In addition, faculty buy-in or required use of the system influence the frequency and manner in which an early alert system is employed at an institution. The type of early alert system, how it is implemented, institutional policy, and commitment to the early alert system - and to student retention broadly - are likely to impact utilization and efficacy of the tool.

Origin of early identification strategies. Early alert systems, as they are known today, aim to identify and engage students who are demonstrating behaviors indicative of failing coursework or dropping out of college (Barefoot, 2004). Such systems were born from an increased focus on retention in the 1970s (Astin, 1987; Varney, 2008). While theories such as Tinto's Interactionalist Theory of Student Departure and Astin's Theory of Student Involvement describe the root of student attrition differently, they generally acknowledge that students are more likely to succeed if they effectively and quickly integrate into the college or university early in their first semester (Astin, 1984; Tinto, 1993).

Accordingly, institutions began to implement retention strategies that were both proactive and reactive (Varney, 2008). Proactive strategies began with a deeper understanding of potential student remediation needs, thereby prompting development of placement tests. Similarly, institutions implemented a number of other initiatives that were intended to effectively introduce students to higher education and assist them in navigating their first year. Examples include first year orientation programs, development of student affairs divisions that focused on academic advising, and orientation programs (Varney, 2008). Each of these strategies represent an institutional focus on student retention through early identification of student needs and intervention.

Complementing the proactive strategies are reactive strategies, which focus on identification of students experiencing distress. Examples include tutoring, student counseling, and early alert systems using intrusive advising (Varney, 2008). Early alert systems, the focus of this study, aim to identify and engage students who are demonstrating behaviors indicative of failing coursework or dropping out of college early in the semester (Barefoot, 2004). In other words, conceptually, early alert systems are aimed to provide interventions early in the semester, when the student has time to change their trajectory and course outcomes. The later in the semester that action is taken, the more history (i.e.: established assignment and exam scores) there is to overcome and less time to do so.

Terminology. The term ‘early warning systems’ was coined by Alexander Astin during the 1970s, a time of budding student attrition theories (Astin, 1987). The terminology, however, around ‘early warning’ and ‘intrusive advising’ has changed with time to reflect a more positive view and included terms such as ‘early alert programs,’(Lupack, 1983) ‘early alert retention systems,’ (Rudmann, 1992), and ‘academic assistance systems’ (Maack, 2001). Institutions will often name their individual systems to ensure positive connotation. For example, in the late 1970s, Miami-Dade Community College was one of the first community colleges to embrace a retention package entitled the 'Student Success System Model' (Keyser, 1989). This model provided a framework to monitor early warning signals and institutional response. Within the framework, students were assessed for course placement and then monitored for program progress and, as needed, counselors and faculty advisors were deployed to provide necessary intervention programs (Keyser, 1989). More recently, the Virginia Community College System implemented an early alert system in 2013, which was named SAILS, an acronym that stands for Student Assistance and Intervention for Learning Success. This system is described in greater detail later in this chapter.

The role of faculty. Historically, many colleges that have depended on student services staff to lead early alert initiatives, placing less onus of such systems - and student retention broadly - on faculty (Barefoot, 2004). The engagement of faculty, however, is critical to student learning and success. Barefoot (2004) asserts that, "We know that although timely feedback on academic performance is motivational for new students, only about 50 percent of instructors provide such feedback" (p. 16). In other cases, faculty identify a student that is experiencing challenges, but then disengage from the process of finding and implementing a resolution. Faculty engagement is strengthened when focusing on learning outcomes, rather than retention, which will inherently follow improved student learning (Barefoot, 2004; Tinto, 1993).

Early alert in the Virginia Community College System. This study focused exclusively on the efficacy of an early alert system employed within the Virginia Community College System (VCCS). The VCCS is a system of 23 independently accredited community colleges that are governed by a statewide governor-appointed board (Code of Virginia, 2016). The centralized nature of the VCCS governance allows for efficiencies in delivery of many information technology-driven services (C. Pfautz, personal communication, July 15, 2016). For example, all of the 23 colleges share one student information system and one learning management system. These shared systems provided a vehicle for the VCCS to launch a common statewide early alert system in 2013. The system is entitled SAILS, an acronym for Student Assistance and Intervention for Learning Success. The system was contracted through a third-party vendor, who worked collaboratively with the VCCS system office to integrate the system with the statewide student information system and learning management system.

In Fall 2013, SAILS was available for use in all developmental education courses (S. Curran, personal communication, July 15, 2016). In Spring 2014, all colleges expanded use of SAILS to include their "gateway courses," which included a handful of high-enrollment freshman-level courses that many students take as initial college-level courses. By Fall 2015, SAILS was available for use in all credit-bearing college courses. All of Virginia's community colleges are required to use SAILS for their developmental and gateway courses; use in other courses is left to the discretion of each college's leadership. Despite all college courses not being required by the VCCS system office to use SAILS, utilization rates are high. In Fall 2015, 84,999 flags were raised.

The VCCS early alert system is a web-based interface that collects student information and provides an easy, online format for faculty to raise flags when they have student concerns. The two triggers within the system that prompt action are flags and kudos (Hobsons, 2016). Flags are electronic warnings triggered by a college faculty or staff member and issued to a student signaling at-risk behavior and institutional resources available for assistance. Conversely, kudos are electronic indicators of good progress or encouragement to keep up good effort. Kudos were not examined in this study. There are seven types of flags and three types of kudos used consistently across all VCCS colleges (S. Curran, personal communication, July 15, 2016). Table 1 indicates the types of flags and kudos used in the VCCS early alert system.

Table 1.

VCCS Early Alert Flags and Kudos

Type	Name
Flag	Attendance Concern
Flag	Never Attended
Flag	Assignment Concerns
Flag	Low Participation
Flag	Low Quiz/Test Scores
Flag	In Danger of Failing
Flag	General Concern
Kudo	Keep up the Good Work
Kudo	Outstanding Academic Performance
Kudo	Showing Improvement

While faculty may raise flags on any of their students at any point in the semester, they are prompted to do so twice in a 16-week semester (S. Curran, personal communication, July 15, 2016). The first prompt occurs a couple of days prior to the college's census date (add/drop deadline), which occurs when 15 percent of the semester has passed, and a couple of days prior to the withdrawal deadline. Faculty prompts come in the form of an online survey emailed to all faculty from college leadership. When the faculty member clicks on the link to the survey, each of their class rosters is displayed. Faculty may quickly and efficiently raise flags, kudos, and customize notes for any of their students and submit. The timing of surveys for courses that are less than 16-weeks in duration have a customized faculty survey schedule.

Six of the seven flags, when raised by a faculty member, trigger an automated email to the student that is customized to the student, the course, the type of flag, and any notes entered by the faculty member (S. Curran, personal communication, July 15, 2016). The email is sent from the faculty member's email address and is automatically signed by them as well. In addition, when a flag is raised, all student support staff that have a "relationship" with the student may view the flag. The relationship is defined by assigned student caseloads or common indicators within the student information system. For example, if a student is a Pell recipient, a relationship is established in the system with the financial aid staff, thereby allowing financial aid staff privileges in the system to view the flag and provide necessary interventions. Each college has a distinct business process for following up and clearing raised flags.

Prior Research in Early Alert Efficacy

In an attempt to address retention rates below 50 percent (NSC, 2015a), institutions across that nation frequently invest in early alert systems (Barefoot, 2004). Despite these significant investments in fiscal and human resources, limited research has been conducted on the efficacy of early alert systems. Bourdon and Carducci (2002) evaluated a number of studies conducted in the 1990's and provided a synthesis of different effective practices, including early alert systems, in community colleges. After evaluating four studies, Bourdon and Carducci (2002) found that early alert systems appear to have a positive effect on completion and re-enrollment. Specifically, the authors stated, "Compared to students who were not involved in such a program, students involved in a nearly alert program:

- Are more likely to successfully complete the course in which they were having academic difficulty
- Maintain higher rates of continuous enrollment by the end of the academic year

- Have higher persistence rates for two or more consecutive semesters
- Exhibit higher persistence rates four years later (including transfer students)" (Bourdon & Carducci, 2002, p. 18).

Despite an early positive report, Bailey and Alfonso (2005) later found that research on the efficacy of various retention programs is lacking in four distinct ways. First, a majority of the research has been conducted in four-year institutions. Thus, the ability to effectively translate these results to community colleges that serve a more diverse, non-residential, working student population is limited. Second, institutional practices and policies are not captured in national datasets that are regularly examined when discussing student success. When information on institutional practices are gathered, they typically focus on a single institution, which lacks generalizability across community colleges. Third, Bailey and Alfonso (2005) assert that the methodology of existing research is typically lacking, in part, due to non-randomized studies that are not able to adequately determine causality. Lastly, research findings are not sufficiently disseminated across community colleges and often go unpublished. "Reports are difficult to obtain and usually include too little information to allow a judgment about the validity of the conclusions" (Bailey & Alfonso, 2005, p. 2).

Compounding the issue of limited valid empirical knowledge on the efficacy of retention programs, the results of existing studies on early alert systems have produced widely-varied results (Brothen et al., 2003; Cai et al., 2015; Hansen et al., 2002; Hudson, 2006; Tampke, 2013). Research results are likely impacted by various forms of early alert systems examined, the setting of the study (i.e., two-year or four-year institution), or targeted student populations (i.e., developmental education students or students taking college-level courses).

Four-year institutions. As noted previously, early alert systems have frequently been studied within the context of a four-year institution setting (Bailey & Alfonso, 2005). For example, Cai et al., (2015) conducted a study that included 611 freshman in a math course at a four-year university. They first examined the relationship between utilization of an early alert system, entitled MavCLASS, and subsequent visits to the tutoring center and then addressed the relationship between visiting the tutoring center and course performance. Their key data points included intervention message data, tutoring center visit data, and course achievement records. Results showed that students visited the tutoring center at a higher rate if they were contacted through MavCLASS and that students that visited the tutoring center experienced better performance in the math class. However, when comparing the course results for those that visited the tutoring center and those that did not, the results are essentially the same. The researchers, however, considered this a positive indicator for the tutoring center because the students that visited the center had higher needs (greater risk) and subsequently performed at equivalent rates is a success. These results, while promising, are evaluating a student population with potentially different work-life schedules thereby making tutoring more accessible than may be experienced by community college students.

While Cai et al., (2015) found a positive impact of the early alert system on course performance in a four-year institution, Hansen et al., (2002) found the early alert system had no impact when evaluating use with students enrolled in a general psychology course. Their quantitative study focused on 240 students enrolled in a course delivered in a non-traditional format, consisting of no lectures and a variety of computerized exercises, exams, etc. Within the study, students that were demonstrating at-risk behaviors (falling behind in coursework or not attending) received an early alert notice. Due to the researchers' interest in also determining the value of having an advisor engaged in the process, there were two treatment groups. Within the first group, only the student received the alert and within the second group, the student and his/her advisor received the alert. The primary purpose of the study was to see if they could positively change student behavior with the implementation of the alerts. The secondary purpose to see the impact of engaging the advisor. The results of the study showed that use of the alert had no statistically significant impact on course performance. Although slight, there was even a decreased course performance for the student/advisor group when compared to the student only group.

Brothen et al. (2003) replicated this study following the deployment of an electronic early alert system that automates much of the notifications to students. The new system was less time-intensive and more user-friendly for faculty, staff, and students. Thus, the researchers had more confidence that students were receiving/reading the notifications. Within the initial study, Hansen et al. (2002) felt that it was unethical to have a randomized control group as that would require denying potential resources to at-risk students. However, because that study showed no impact, the risk of employing a randomized control group was lessened, if not eliminated in the 2003 study. Thus, they employed a control group that consisted of student that did not receive an early alert notice.

The results of this subsequent study were consistent with the first – the early alert system did not have a statistically significant impact on student success. Although the results are not promising for early alert systems, the researchers conclude the study with reasons that continuation of the system may be worthwhile, including: enhancing communication and trust between faculty and staff, letting students know that faculty and staff are aware and concerned with their performance, and students were unable to claim they were unaware that they were not doing well. The researchers stopped short of indicating whether these reasons justify the cost of the system.

While Cai et al. (2015), Hansen et al. (2002), and Brothen et al. (2003) each examined some indicator of efficacy of an early alert system, they did so within the context of a specific course at a four-year institution. In 2013, Tampke quantitatively assessed the impact of an early alert system across the broad student population at a large public university. The system Tampke studied integrated with the student information system and provided the following key features: faculty access to the system, faculty referrals within the system, storage of data/usage, and recording student contacts and outcomes. At the end of the first term of use, 87 faculty had referred 255 students, with reasons for the referral varying. Tampke used a chi square analysis with demographic data of control and treatment populations. The results included data on: grades from referred courses, cumulative grade point average, term grade point average, and re-enrollment. Roughly 21 percent of the referred students passed the course in which they received a referral with a grade of C or higher. The researcher, however, recognizes that there is no “like” group at the campus and thus comparing the control group (no referral) and general college population does not measure efficacy of the early alert system. An in-group analysis (chi square), however, did indicate that the type of intervention effects re-enrollment and success outcomes. Following a one-way ANOVA, the author found that personal interventions had a statistically significant positive impact on success.

While Tampke’s (2013) study demonstrates modest positive results, it is imperative to note that the population studied consisted of the broad set of students served by the university, including new or continuing first-time-in-college students, transfer students, and even graduate students. Thus, the researcher's findings, while valuable within the context provided, offer significant limitations in comparing to a two-year institution setting.

Developmental education. One of the characteristics that is often used to delineate community colleges from four-year institutions is the presence of developmental education and students who are academically underprepared for college-level courses. Interestingly, however, in 2006, Hudson studied an early alert system implemented at Morehead State University, a four-year institution offering developmental education courses. It is estimated that of the 1,050 freshmen students at Morehead State University at that time, 20 percent who fail courses do so because they are chronically missing class. In response, an early alert system, implemented in 2003, was designed to report student absences, contact students, and track their progress after contact was made. Ultimately, the goal of the system was to enhance course success rates by reducing absenteeism. The online system reported and made contacts during the 2nd, 4th, and 6th week of the semester. In the study, Hudson (2006) targeted,

> only those freshman students who 1) were enrolled in twelve or more semester hours, 2) who were enrolled in a developmental education course, 3) who were enrolled in an entry level course for a specific major, and 4) who were reported as having excessive class absences during the 2nd, 4th, or 6th week of classes. (p. 221).

After reviewing enrollments, transcripts, and withdrawal/add/drop rates, Hudson conducted a comparative analysis "to determine if the intervention method (contact or counseling) resulted in significant difference in the pass/fail rates or the drop/add rates of students who had been reported with excessive absenteeism problems" (Hudson, 2006, p. 221).

216 students were reported as having excessive absenteeism, and 108 of them were contacted. Of those contacted, 91 responded to the contact made by the college. Of those 91, 44

passed the course, resulting in a 48 percent success rate. The author then describes ten implications for retention, including assertions that early alert systems can enhance retention activities and that such systems do impact pass/fail rates.

The limited research on the impact of early alert system within community college settings has focused almost exclusively on impact on performance of developmental education students. It is widely recognized that there is a high need for developmental education among community college students, particularly in mathematics (Wladis et al., 2014). This persistent need has recently been complemented by a trend to couple remedial coursework with technology. Thus, a large, diverse, urban community college revised their remedial mathematics curriculum in 2009 to integrate the use of technology and an early alert system. The early alert portion was driven by students' mid-term score, which prompted interventions for students scoring below 70 percent that required them to engage in additional online practice problems and other academic interventions. When evaluating the efficacy of the new system, Wladis et al., (2014) hypothesized that,

> Using a department-wide midterm as an early-alert system to identify at-risk students in remedial mathematics classes and then requiring students who fail the midterm to complete online elaborate-feedback intervention assignments will raise course passing rates and student passing rates on the university-wide final exam.…The amount of time that students spend on the intervention assignments will be positively correlated with course and final exam passing rates. (p. 1086)

Wladis et al. (2014) used a quasi-experimental, historically-controlled design and compared the intervention's effects on the passing rate of students in remedial courses with earlier years. Because the researchers examined five semesters, the sample size of the study was 21,221 students. The researchers found that the,

> Passing rates improved by a significant margin in all remedial classes when comparing pre- to post-intervention fall-over-fall and spring-over-spring. While most of the gains were obtained during the first year of the intervention, further improvements were also seen during each observed semester of the intervention. (p. 1090)

In fact, passing rates were as much as 50 percent higher than previous semesters (Wladis et al., 2014).

While the results are very promising, it is also critical to note that these results may have been influenced by multiple variables, including an intentional effort at the college to reform developmental mathematics and faculty engagement in that process. Thus, while this study demonstrates significant success of the system implemented at the institution studied, generalizability to institutions engaging in unique forms of developmental education redesign and implementation of early alert systems is limited.

Further supporting Bailey and Alfonso's (2005) assertion that much of the research conducted on efficacy of retention programs goes unpublished, there is additional research conducted as part of unpublished doctoral dissertations that evaluate the efficacy of early alert systems with community college developmental education students. For instance, Simpson (2014) evaluated the impact of an early alert system for community college students enrolled in at least one developmental education course. Using a mixed method study, the researcher first used a quantitative, quasi-experimental ex post facto with non-randomization design to determine retention and completion of first-time, full-time students enrolled in developmental education that were identified by the early alert system. Subsequently, Simpson (2014) used qualitative data to further understand the quantitative results. More specifically, the researcher 1) explored if the early alert system impacted success rates in developmental education courses, 2) compared the semester-to-semester and one-year persistence rate for those impacted and not impacted by the early alert system, and 3) how the college experience surrounding the early alert initiative impacted student success, persistence, and retention.

Analysis of the quantitative data provided results that were not statistically significant. Qualitative data, however, provided information about areas for potential improvement, including: "students did not know how to connect with the support services…, students encountered a decentralized process…, a need for better timing of communication and collaboration…, faculty did not have a robust tracking system to provide feedback" (p. 84).

Like the aforementioned studies, results on the efficacy of early alert systems are mixed. Where quantitative results for Simpson (2014) were not statistically significant, another doctoral student, Green (2015), found the relationship between use of an early alert system and student grades in developmental English courses at a Mid-Atlantic urban community college were positive and statistically significant. However, the relationship was not statistically significant when evaluating persistence.

In sum, much of the research conducted on the impact of early alert systems has been done within the context of a four-year institution, or when applied in a two-year college, focused almost exclusively on targeted student populations, such as those enrolled in developmental education courses. Further limiting the influence of existing research on early alert systems are the mixed results across studies.

Justification for Study

In response to new calls for student success and accountability, institutional leaders have invested in a plethora of strategies to serve a diverse student body and improve student outcomes, primarily focusing on first-year students (Barefoot, 2004). These strategies, driven by retention theory, are often defined by initiatives such as first-year orientations, student success courses, learning communities, structured pathways, open educational resources, and early alert systems. However, advancing theory to action in a manner that engages students and significantly impact retention rates has proven difficult (Tinto, 2007; 2012). Evaluation of these initiatives – understanding what works, how it works, and why it works - is imperative to making meaningful institutional investments in student success.

As noted above, there is limited existent research on the efficacy of early alert systems and where there are results, they are collectively inconclusive. This study adds to the body of knowledge and informs community college leaders and policymakers about the impact of an early alert system on student persistence. The results further inform institutional leaders about how to target fiscal and human resources where they may anticipate the greatest impact on student success.

Summary

This chapter began with a review of literature on college student retention, including Tinto's Interactionalist Theory of Student Departure, which provides a theoretical framework for early alert retention systems. Special attention was given to retention within a community college context, including a new, dual mission that places student success at the focus of national initiatives and, in many cases, funding models. Despite the relatively recent shift in focus to student success, community colleges face persistent challenges in effectively moving the needle on student retention due to, at least in part, a significant dependency on adjunct faculty, and the unique make up and challenges facing community college students.

The completion movement has prompted a booming retention industry that focuses on initiatives and products designed to increase student persistence and completion (Barefoot, 2004). Early alert systems are one component of this industry and have been widely applied – in various forms – in colleges and universities across the nation. Despite pervasive use and dedication of human and fiscal resources to support early alert systems, little empirical evidence points to efficacy (or lack thereof) of such systems.

Thus, lastly, an overview of existing research on the efficacy of early alert systems was provided. The studies have largely taken place at four-year institutions or, when at a community college, have a strong focus on developmental education students. Further, the findings of the research has been largely inconclusive, and called for additional research to add to the body of knowledge and provide insight to institutional leaders about a continued investment in early alert retention systems. The methodology for this study is presented in Chapter 3.

CHAPTER 3

METHODOLOGY

Previous research on early alert systems in community colleges has focused almost exclusively on developmental education students (Simpson, 2014; Wladis et al., 2014), thereby creating a gap in knowledge on the efficacy of such tools with students enrolled in college-level courses. Additionally, previous studies have produced inconsistent findings. Using a quasi-experimental quantitative methodology with matched control groups, this study examined the impact of an early alert system on community college students enrolled in college-level coursework as well as developmental mathematics and developmental English. Further, the effect of the number of flags raised per student (dosage) on persistence was studied. The purpose of this study was to examine the relationship between the use of an early alert system and persistence for students taking developmental education courses and students taking college-level courses in the Virginia Community College System.

This chapter articulates the research design, research questions, the setting and participants, data collection procedures, and a description of the data analysis process. Lastly, the chapter will conclude with a discussion of the study's limitations.

This study was guided by the following research questions:

1. What impact does the number of *Academic* flags have on student persistence to the next semester?
    - 1a. What impact does the number of *Academic* flags raised in a college-level course have on student persistence to the next semester?
    - 1b. What impact does the number of *Academic* flags raised in a developmental English course have on student persistence to the next semester?

1c. What impact does the number of *Academic* flags raised in a developmental mathematics course have on student persistence to the next semester?

2. What impact does the number of *Attendance* flags raised have on student persistence to the next semester?

2a. What impact does the number of *Attendance* flags raised in a college-level course have on student persistence to the next semester?

2b. What impact does the number of *Attendance* flags raised in a developmental English course have on student persistence to the next semester?

2c. What impact does the number of *Attendance* flags raised in a developmental mathematics course have on student persistence to the next semester?

3. What impact does the number of *In Danger of Failing* flags raised have on student persistence to the next semester?

3a. What impact does the number of *In Danger of Failing* flags raised in a college-level course have on student persistence to the next semester?

3b. What impact does the number of *In Danger of Failing* flags raised in a developmental English course have on student persistence to the next semester?

3c. What impact does the number of *In Danger of Failing* flags raised in a developmental mathematics course have on student persistence to the next semester?

4. What impact does the number of flags raised have on developmental education student persistence to the next semester?

4a. What impact does the number of flags raised have on developmental mathematics student persistence to the next semester?

4b. What impact does the number of flags raised have on developmental English student persistence to the next semester?

Research Design

The researcher used a quantitative, quasi-experimental, non-randomized research design with matched-control groups to respond to each of the research questions. The non-randomized design reflected that the treatment and control group were not randomly selected, but were created based upon the participant's interaction, or lack thereof, with the early alert system. For instance, if a student received an early warning flag, the student was automatically placed in the treatment group. Students not receiving a flag were placed in the control group. The treatment group was limited to those students receiving flag(s) in a 16 week course during the Fall 2015 semester.

A matched control group was implemented for each research question to address the confounding variables introduced through a non-randomized design. The control groups strengthen the research design by mimicking random assignment. The treatment and control group were matched on similar attributes as determined by the variables shown in Table 2. Additional detail on the matching process is provided below.

A quasi-experimental design attempts to control for some confounding variables, but is not able to account for all possible variables that could impact the outcome (Leedy & Ormrod, 2016). Thus, as was the case with this study, alternative explanations for the results cannot be ruled out. The employed research design, however, is a widely accepted and rigorous design and is further enhanced by creating the matched control group, mimicking a true experimental design.

Table 2.

Description of Matched Factors

Covariate	Description	Coding
Pell-recipient	Students received a federal Pell Grant. The Pell Grant is a federal, need-based grant that students do not have to repay.	0=not Pell-recipient; 1=Pell-recipient
First-generation status	Students who indicate that both parent(s)/legal guardian(s) have no more than a high school diploma. If either parent/legal guardian has at least some college, or if the student only lists one parent/legal guardian, the student is not identified as having first-generation status.	0=not first-generation; 1=first-generation
Full- or part-time status	Full time students are enrolled in 12 or more credits in the fall semester. Part-time students are enrolled in 11 or fewer credits in the fall semester.	0=part-time; 1=full-time
Age	Years since date of birth	0=24 years old or less; 1=25 years old or more

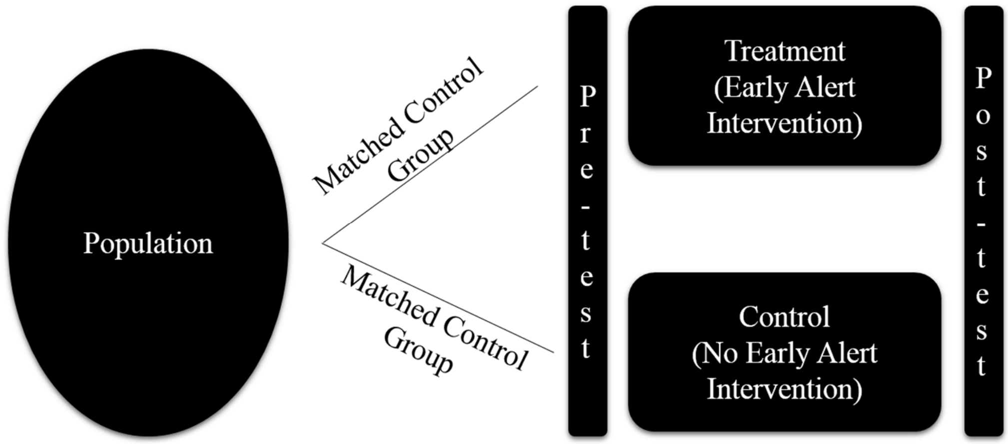

Figure 1. Research design.

Setting

This study was conducted using data derived from the VCCS Office of Institutional Research and Effectiveness (OIRE). The VCCS is a centralized system of 23 community colleges in Virginia. While each college is individually accredited, the system is governed by a governor-appointed State Board for Community Colleges.

The 23 colleges share a common student information system and each are required to employ the same early alert technology, SAILS, which stands for Student Assistance and Intervention for Learning Success. In Fall 2013, all colleges were required to use SAILS with their developmental education courses. Subsequently, in Spring 2014, this requirement expanded to include all gateway courses, including entry-level college math and English courses. Colleges are not required to use it across all other college-level courses, though usage is widespread with 84,999 flags raised in the Fall 2015.

The VCCS provided an optimal environment for evaluating the efficacy of the early alert system for a number of reasons. First, each college is required to use the same seven types of flags provided within the system, allowing for examination of the effect of flag type on student success and persistence across 23 colleges. For purposes of this study, the seven flag types were categorized into four groups:

1) *Academic*, consisting of the Low Participation, Low Quiz/Test Scores, and Assignment Concerns flags,
2) *Attendance*, consisting of the Never Attended and Attendance Concerns flags,
3) *In Danger of Failing*, which is solely comprised of the singular *In Danger of Failing* Flag, and
4) *General Concern*, which is solely comprised of a singular *General Concern* flag.

The *In Danger of Failing* flag signals that a student is on the verge of failing and will likely do so without immediate intervention. The cause of the potential failure is not identified with this flag, but signals to college staff that quick action is required. The fourth group of flags, *General Concern*, is typically raised in instances of very sensitive concerns or information about a student and is generally handled outside of the technological features of SAILS. Due to the limited information about the stimuli for raising a *General Concern* flag, it was excluded from the first three research questions, but was included when examining the impact of dosage in the fourth research question.

The second reason the VCCS was selected for this study was the consistency of application of the SAILS system in 16-week courses. For all courses that run on a 16-week schedule, the VCCS requires distribution of two faculty surveys during the term, prompting faculty to raise flags. The first survey is emailed to faculty just before the college's census date, which occurs approximately two weeks into the semester. The second is a few days prior to the college's withdrawal deadline, occurring when the course is 60 percent complete (Virginia Community College System Policy Manual, 2016). Again, this consistent application of SAILS in 16-week courses provides a level of continuity within the data to enhance evaluation of outcomes across a broad population.

Third, extensive application of SAILS across the 23 colleges provides a large population of students and their outcomes to be evaluated, thereby increasing the validity of the study. Lastly, the consistency of data and variables across the institutions, gathered from a common student information and early alert system, enhanced reliability and validity of the study.

Human Subjects Review and Data Collection Procedures

Approval to conduct the study was received from the Old Dominion University Education Human Subjects Review Committee, as required, for all studies involving human subjects. The data used in this study were existent and de-identified allowing the researcher to submit an application requesting exemption category 6.4. Per Old Dominion University's Institutional Review Board (IRB) requirements, the researcher and principal investigator also updated the required certification demonstrating satisfactory completion of the Collaborative Institutional Training Initiative program. The approval letter is found in Appendix D.

After receiving approval, data were collected from the VCCS OIRE and consisted entirely of existing data. Data were collected in January 2017 using the established VCCS data request process. The VCCS OIRE removed all student names and assigned a unique identifier to maintain student confidentiality. Although data were collected via the VCCS OIRE, the primary source of data may be found in Table 3. All data provided by the VCCS OIRE were received in a secure Microsoft Excel file. Once collected, variables were coded to facilitate analysis.

Table 3.

Data Primary Source

Data Category	Data Element	Primary Source
Student Characteristics	Course enrollments	VCCS Student Information System
	First-time-in-college status	VCCS Student Information System
	Program-placed	VCCS Student Information System
	First-generation status	VCCS Student Information System
	Pell-recipient status	VCCS Student Information System
	Full- or part-time status	VCCS Student Information System
	Age	VCCS Student Information System
	Semester grade point average*	VCCS Student Information System
	Race**	VCCS Student Information System
	Gender**	VCCS Student Information System
Student Outcomes	Persistence within the VCCS	VCCS Student Information System
	Persistence in higher education, external to the VCCS	National Student Clearinghouse
	Graduation	VCCS Student Information System
Early Alert Flags	Raised flag by type, student and course	VCCS SAILS System

**The mean semester grade point average for each treatment and control group were provided to offer greater context and comparisons.*

***Gender and race were collected in order to provide more detailed descriptive statistics of the control and treatment groups.*

Participants

The population for this study consisted of all students who were program-placed and enrolled in at least one 16-week course in Fall 2015. The population parameters were selected to strengthen the validity of the study's findings. Program-placed students are those pursuing a degree, certificate, diploma, or career studies certificate, as indicated in the VCCS student information system. Students without such an indicator or dual-enrolled high school students are not program-placed. Thus, only program-placed students were included in the study to avoid examining students who are intentionally enrolled for a short-time and without a long-term academic goal.

Further, the VCCS offers a variety of course lengths in a semester, though the 16-week course is the most common and traditional path. The duration of a course would have a direct impact on when and how many times faculty are prompted to raise flags within the SAILS system, and therefore, using varied course lengths within the study would minimize consistent application of SAILS within the treatment group. Therefore, the population parameters focused the scope of the study to increase the likelihood for enhanced validity of findings.

Although 84,999 flags were raised during the Fall 2015 semester, 24,001 of the flags were not associated with a course enrollment in the data file. The absence of course enrollment data for these flags indicates that the student dropped the course prior to the college's add/drop deadline (census date), which removes evidence of enrollment in the course from the student record. In other words, the data show a flag was raised, but the course in which it was raised is unknown and, thus, analysis by course enrollment is not feasible. After removing the 24,001 flags without course enrollment data, 60,998 records were remaining for analysis. The stimulus for the student dropping the course and the course type (college-level, developmental English, or developmental mathematics) are unknown and therefore may not be factored into the study. When the data were further refined to only include flags raised in a 16 week course, the total number of records for the study was 48,814. This figure represents the number of flags raised, which is a duplicated student headcount. For example, a single student (headcount of one) may receive three flags (three flags (duplicated) = 1 student (unduplicated)). The total number of flags (duplicated headcount) and students (unduplicated headcount) for the categories examined in each research question is provided in Table 4.

Table 4.

Number of Flags and Unduplicated Student Headcount for Each Research Question

Research Question	Flag Type	Course Enrollment	Number of Flags (Duplicated Headcount)	Number of Students (Unduplicated Headcount)
1a	*Academic*	College-level	21,663	13,747
1b	*Academic*	Developmental English	891	671
1c	*Academic*	Developmental Math	997	771
2a	*Attendance*	College-level	8,777	6,276
2b	*Attendance*	Developmental English	563	509
2c	*Attendance*	Developmental Math	332	262
3a	*In Danger of Failing*	College-level	11,827	8,876
3b	*In Danger of Failing*	Developmental English	495	443
3c	*In Danger of Failing*	Developmental Math	456	413
4a	All	Developmental English	2,082	1,163
4b	All	Developmental Math	1,923	1,068
1-3	None	College-Level	N/A	108,195
1-4	None	Developmental English	N/A	4,224
1-4	None	Developmental Math	N/A	1,445

Variables

Within the context of this study, the impact of the early alert system on student persistence was examined. The independent and dependent variables within the four research questions are detailed in Table 5.

Table 5.

Independent and Dependent Variables

Research Question	Name	Description	Variable	Type
1	Dosage	The number of *Academic* flags raised per student	Independent Variable	Continuous
1	Student Persistence	Student enrollment in Spring 2016 at VCCS or another institution, or graduation	Dependent Variable	Categorical
2	Dosage	The number of *Attendance* flags raised per student	Independent Variable	Continuous
2	Student Persistence	Student enrollment in Spring 2016 at VCCS or another institution, or graduation	Dependent Variable	Categorical
3	Dosage	The number of *In Danger of Failing* flags raised per student	Independent Variable	Continuous
3	Student Persistence	Student enrollment in Spring 2016 at VCCS or another institution, or graduation	Dependent Variable	Categorical
4	Dosage	The number of flags (regardless of flag type) raised per student	Independent Variable	Continuous
4	Student Persistence	Student enrollment in Spring 2016 at VCCS or another institution, or graduation	Dependent Variable	Categorical

Course enrollment data indicated if the flag was raised in a course that was developmental English, developmental mathematics, or college-level. Each VCCS course was labeled with a three letter prefix and number. The following VCCS course prefixes represent a developmental education course: ENF (English), MTE (mathematics), and MTT (mathematics).

Courses with the prefix BSK (Basic Skills) were eliminated from the data because they represent courses that fall below the lowest developmental education course level. All other course prefixes represent a college-level course.

Independent and dependent variables. The independent variable in each research question is the number of flags raised (dosage), per student. The first three questions examine the number of *Academic*, *Attendance*, and *In Danger of Failing* flags, respectively, raised in college-level, developmental English, and developmental mathematics courses. The last flag type – *General Concern* – was only be used when determining dosage in the fourth research question for developmental English and developmental mathematics courses.

The dependent variable for each research question was persistence to the next semester. If a student re-enrolled in the VCCS in Spring 2016, graduated in December, 2015, or transferred to another institution of higher education, they were considered to have persisted. If they failed to meet one of these three conditions, they were considered not to have persisted. The three forms of persistence are shown in Table 6.

Table 6.

Dependent Variable Coding

Research Question	Source	Form of Persistence	Coding
1-4	VCCS Student Information System	Re-enrollment in VCCS in Spring 2016	0=no persistence in VCCS; 1=persist in VCCS
1-4	VCCS Student Information System	Graduation in December 2015	0=no graduation; 1=graduation
1-4	National Student Clearinghouse	Transfer to another institution of higher education	0=no transfer; 1=transfer

Data Analysis

After receiving the data from the VCCS OIRE, each variable was coded for analysis. The researcher organized and analyzed the data using IBM SPSS Statistics 24. The data representing the treatment groups (those with at least one flag raised) were provided by the VCCS with a row of data for each flag raised; thus, the researcher aggregated the files to reflect one row per student and created a variable indicating the sum of the number of flags raised per student. This allowed the researcher to accurately capture descriptive statistics, by student, on demographics and retention and also to run the required binary logistic regression analyses. The total number of cases in each treatment and control group is provided in Table 4.

Each data set was first analyzed for descriptive statistics for each of the variables noted in Table 2 and additional demographic information, including race, gender, and semester (Fall 2015) grade point average. These descriptive statistics are provided in Tables 22-26 in Appendix E.

Matched control groups. The validity of the study's results were enhanced by creating control groups mimicking random assignment using the matched factors described in Table 2. There were four matched factors, which were collected from the VCCS student information system. Each student was identified with a binary indicator for Pell-recipient, first-generation, full- or part-time status, and age (24 years or less; 25 years or greater). Creating the control groups on these factors reduced bias and is complimentary to regression-based data analysis (Stuart & Rubin, 2008). A detailed description of the analysis is provided below.

With four binary covariates, there were sixteen possible combinations (strata) of an individual student's characteristics represented by the matched factors. In order to ensure that the treatment and control groups were not statistically different, an additional variable representing the strata one through sixteen was created. The sixteen strata are shown in Table 7. Using IBM SPSS Statistics 24, each student record was then categorized into a strata according to the student characteristics represented in the matched factors.

Table 7.

Matching Strata

Strata	Age	Pell-Recipient	Full-Time/ Part-Time	First Generation
1	1	1	1	1
2	1	0	1	1
3	1	1	0	1
4	1	1	1	0
5	0	1	1	1
6	1	1	0	0
7	1	0	0	1
8	0	0	1	1
9	0	1	1	0
10	0	1	0	1
11	1	0	1	0
12	0	0	0	1
13	0	0	1	0
14	0	1	0	0
15	1	0	0	0
16	0	0	0	0

To further determine the strength of the matched groups, a chi square analysis was conducted in order to see if the groups were alike on variables not included in the strata – gender and race. More specifically, for each of the first three research questions, the strata were analyzed for three groups – developmental English, developmental mathematics, and college-level. In the fourth research question, the strata were analyzed for developmental English and developmental mathematics. In this study, a preponderance of the analysis of the strata were alike for all developmental English and developmental mathematics groups, further demonstrating the similarity of the treatment and control groups. The college-level groups showed some differences within the strata. Thus, additional analyses were conducted in order to confirm similarity of the college-level treatment and control groups. The analysis consisted of running binary logistic regressions with and without the gender and race variables. Findings indicate adding gender and race to the model have little to no impact on the outcome. Detailed findings from the chi square analysis are provided in Appendix F and findings from the additional binary logistic regression analysis on college-level groups is provided in Appendix G.

After creating and confirming the matched control groups, analysis was conducted using separate multiple binomial logistic regression models. A regression model was selected in order to predict an outcome based on a number of variables. Regression analysis, often used in social sciences, "is a way of predicting an outcome variable from one predictor variable (simple regression) or several predictor variables (multiple regression)" (Field, 2009, p. 198). Notably, typical regressions require that the dependent variable be continuous and unbounded. In this study, the dependent variable – student persistence - in each research question is dichotomous. Logistic regression, an extension of regression analysis, provided a means to predict categorical outcomes based on predictor variables that are continuous or categorical (Field, 2009). Further, binomial (binary) logistic regression is appropriate when only two categorical outcomes exist. Thus, due to the binary outcomes of each of the four research questions, a binomial logistic regression was used with each research question.

Statistical assumptions. Seven assumptions underlie binomial logistic regression analysis; these assumptions were affirmed to verify that the statistical analysis is aligned to the study design and to validate the findings (Laerd Statistics, 2016). Four of the assumptions were necessary to confirm the choice of the research design and corresponding measurements. The remaining three assumptions were tested using SPSS to validate the study findings.

The first assumption of a binomial logistic regression is that there is only one dependent variable, which has two possible outcomes (Laerd Statistics, 2016). In this study, this assumption was satisfied as the dependent variable – student persistence – is dichotomous. A student either persisted or did not. The second assumption asserts that the independent variables are either continuous or nominal. Each of the independent variables in this study is continuous.

The third assumption requires that each observation is independent of the population (Keith, 2015; Laerd Statistics, 2016). Further, each of the dependent variables and all of the nominal (categorical) independent variables are mutually exclusive (Laerd Statistics, 2016). Each student outcome within this study was not influenced by the outcome of other students in the population, and the dependent variable was mutually exclusive. For example, it is not possible for a student both persist and not persist. Therefore, this assumption was validated.

The fourth assumption addresses the size of the data and requires at least 15 cases per independent variable. The data set for this study far exceeded 15 cases. Specifically, each research question contains one independent variable and the number of cases (students) in the treatment groups ranged from 262 to 13,747. The reliability of binomial logistic regression analysis is significantly enhanced with greater sample size (Laerd Statistics, 2016). The satisfaction of these first four assumptions affirmed binomial logistic regression as a proper statistic test for data analysis.

The fifth assumption states that "there should be no significant outliers, high leverage points or highly influential points" (Laerd Statistics, 2016, p. 5). This means that there should not be observations that stray so far from the norm that they adversely influence the outcomes of the regression line. Using IBM SPSS Statistics 24, this assumption was tested using descriptive statistics to identify any cases that were more than three standard deviations from the mean. Any outliers were then adjusted to the plausible high (outliers removed) number of flags raised in the data set. Table 8 indicates the number of outliers and the plausible high for each research question.

Table 8.

Number of Outliers and Plausible High Number of Flags Raised Per Student

Research Question	Course Enrollment	Number of Outliers	Plausible High
1a	College-Level	315	4
1b	Developmental English	8	3
1c	Developmental Mathematics	2	3*
2a	College-Level	82	4
2b	Developmental English	1	3*
2c	Developmental Mathematics	8	3
3a	College-Level	166	3
3b	Developmental English	2	3*
3c	Developmental Mathematics	1	3*
4a	Developmental English	16	5
4b	Developmental Mathematics	18	5

**a plausible high of three flags exceeds three standard deviations from the mean, but was used in order to determine linearity and to reflect the reasonableness of a student receiving three flags.*

The next assumption requires that the data not show multicollinearity. In other words, when two independent variables are strongly related to each other, potential arises for a lack of knowledge as to which independent variable accounts for the outcome. In the case of the developmental English and developmental mathematics groups, there is only one independent variable per research question and thus this assumption does not apply. For the college-level groups, the matched control group was analyzed using gender and race and the assumption was affirmed.

Finally, the seventh assumption, asserts that "there needs to be a linear relationship between the continuous independent variables and the logit transformation of the dependent variable" (Laerd Statistics, 2016, p. 5). In this case, linearity of the continuous variables with respect to the logit of the dependent variable was assessed via the Box-Tidwell procedure was used to confirm that this assumption was met (Laerd Statistics, 2016). A Bonferroni correction was applied using all three terms in the model resulting in statistical significance being accepted when $p < .1667$. The p value for each research sub-question is noted in Table 9. Based on this assessment, the independent variables for eight of the groups were found to be linearly related to the logit of the dependent variable. The three remaining groups - represented in research questions 1b, 2a, and 3a - failed to meet the linearity assumption. Given the sample size of the groups, however, the Central Limit Theorem may be applied. This Theorem states that regardless of the distribution of the population, if the population size is large enough (generally greater than 30), one can assume a normal distribution in the parameter estimates (Field, 2009). In other words, as a sample size increases, the distribution of parameters (i.e., sample means) normalizes.

Table 9.

Linearity of Independent Variables (p value)

Research Question	Course Enrollment	*p* value
1c	College-Level	.695
1a	Developmental English	.118
1b	Developmental Mathematics	.325
2c	College-Level	.044
2a	Developmental English	.811
2b	Developmental Mathematics	.747
3c	College-Level	.086
3a	Developmental English	.541
3b	Developmental Mathematics	.646
4a	Developmental English	.545
4b	Developmental Mathematics	.809

Limitations

Although this study presented strength in its data and design, it also has a number of limitations to the internal validity. Internal validity refers to "the extent to which its [the study's] design and the data it yields allow the researcher to draw accurate conclusions about cause-and-effect and other relationships within the data" (Leedy & Ormrod, 2016, p. 85). Within this study, internal validity may be threatened by the lack of random-assignment. Due to the nature of existing data and ethical concerns about withholding early alert interventions to students demonstrating need, no opportunity presents itself for random-assignment nor a pre-test. To combat this limitation, a matched control group was established using the four matched factors identified in Table 2 to ensure similar sample composition.

An additional limitation to the study is the subjectivity associated with when a faculty member chooses to raise a flag. The VCCS asks faculty to use their judgment in determining when a flag is or is not warranted and thus, individual faculty thresholds for academic performance influence when a student is formally engaged in the early alert system. For example, one faculty member may be inclined to wait for three absences before raising a flag, whereas another may make this determination based upon whether or not they received advanced notice from the student with a plan to make up the missed class. This limitation was minimized by the volume of faculty engaged in the system across 23 colleges and the number of flags raised.

Conclusion

The purpose of this study was to examine the relationship between the use of an early alert system and persistence for students taking developmental courses and students taking college-level courses in the VCCS. A quasi-experimental, non-randomized design was employed and a matched control group was used to reduce selection bias and enhance the validity of the results. Further, the binary outcomes for each of the dependent variables allowed for multiple binomial logistic regressions to respond to the four research questions. While the study employed a large population and is supported by common data measures across the population, the study did present limitations to the internal and external validity. A detailed description of the results of the results is provided in Chapter 4. In addition and wherever possible, data has been reported in tables, graphs, figures, and narrative form to most effectively communicate the findings.

CHAPTER 4

RESULTS

The dependent variable – student persistence – in each of the four research questions was dichotomous; therefore, a binary logistic regression was used. The predictor (independent) variable - the number of flags the student received - was continuous. Results of the logistic analysis for each research question are provided below.

Research Question 1

Research question one examined the impact the number of *Academic* flags had on student persistence to the next semester. Specifically, this impact was evaluated for students enrolled in college-level courses, developmental English, and developmental mathematics.

College-level. The results of the analysis provided a statistically significant model, $X^2(1, N = 118{,}945) = 337.524$, $p < .001$. The Nagelkerke R square indicates that the model accounted for .4 percent of the total variance. This suggests that the predictor variable (number of *Academic* flags raised) has a very weak relationship with prediction of those that persisted and those who did not. Prediction success was 0 percent for those that did not persist, but 100 percent for those that did persist. The beta for the independent variable was positive suggesting a positive impact on persistence. The expected beta (odds ratio) suggests that for every *Academic* flag raised in a college-level course (up to four), a student is 1.2 times more likely to persist. Table 10 presents the regression coefficients (B), the Wald statistics, significance level, odds ratio [Exp(B)], and the 95 percent confidence intervals (CI) for odds ratios (OR) for the predictor.

Table 10.

Logistic Regression Results for Predicting Whether the Number of Academic flags Raised for College-Level Students Impacts Persistence

Step	Variable Entered	B	Wald	Significance	Exp(B)	95% C.I. for Exp(B)	
						Lower	*Upper*
1	Number of *Academic* flags Raised	.200	318.405	.000	1.221	1.194	1.248
	Constant	.363	3,448.762	.000	1.438		

Developmental English. The results of the binary logistic regression provided a statistically significant model, $X^2(1, N = 4{,}895) = 51.489$, $p < .001$. The Nagelkerke R square indicated that the model accounted for 1.4 percent of the total variance. Prediction success was high (90 percent) for those that did not persist, but only 17.6 percent for those that did persist. The beta for the independent variable was positive suggesting a positive impact on persistence. Further, the expected beta (odds ratio) suggests that for every *Academic* flag raised (up to three flags), a student is 1.532 times more likely to persist. The regression coefficients (B), the Wald statistics, significance level, odds ratios [Exp(B)], and the 95 percent confidence intervals (CI) for odds ratios (OR) for the predictor may be found in Table 11.

Table 11.

Logistic Regression Results for Predicting Whether the Number of Academic flags Raised for Developmental English Students Impacts Persistence

Step	Variable Entered	B	Wald	Significance	Exp(B)	95% C.I. for Exp(B)	
						Lower	*Upper*
1	Number of *Academic* flags Raised	.427	48.451	.000	1.532	1.359	1.727
	Constant	-.121	15.758	.000	.886		

Developmental mathematics. Results of the logistic regression indicated that the predictor model provides a statistically significant and positive impact on persistence over the constant model. $X^2(1, N = 2{,}216) = 1{,}087.753, p < .001$. The Nagelkerke R square indicates that the model accounted for 55 percent of the total variance. This suggests that the predictor variable (number of *Academic* flags raised) has a moderately strong relationship with predicting persistence. Prediction success was high (88.9 percent) for those that did not persist, as well as for those that did persist (89.7 percent). The beta for the independent variable was positive suggesting a positive impact on persistence. Further, the expected beta (odds ratio) suggests that for every one *Academic* flag raised (up to three), a student is 19 times more likely to persist. Table 12 presents the regression coefficients (B), the Wald statistics, significance level, odds ratio [Exp(B)], and the 95 percent confidence intervals (CI) for odds ratios (OR) for the predictor.

Table 12.

Logistic Regression Results for Predicting Whether the Number of Academic flags Raised for Developmental Mathematics Students Impacts Persistence

Step	Variable Entered	B	Wald	Significance	Exp(B)	95% C.I. for Exp(B)	
						Lower	*Upper*
1	Number of *Academic* flags Raised	2.946	607.775	.000	19.033	15.058	24.056
	Constant	-2.419	659.500	.000			

Research Question 2

Research question two examined the impact the number of *Attendance* flags had on student persistence to the next semester. Specifically, this impact was evaluated for students enrolled in college-level courses, developmental English, and developmental mathematics.

College-level. Results of the analysis provide a statistically significant model, $X^2(1, N = 111{,}474) = 16.578$, $p < .001$. The Nagelkerke R square indicates that the model does not account for the total variance (0 percent). This suggests that the predictor variable (number of *Attendance* flags raised) has a weak relationship with prediction of those who persisted and those who did not. Prediction success was 0 percent for those that did not persist, but 100 percent for those that did persist. The beta for the independent variable was negative suggesting a negative impact on persistence. With an expected beta (odds ratio) of .933, for every *Attendance* flag raised (up to four), a student is 1.1 times less likely to persist. Table 13 presents the regression coefficients (B), the Wald statistics, significance level, odds ratio [Exp(B)], and the 95 percent confidence intervals (CI) for odds ratios (OR) for the predictor.

Table 13.

Logistic Regression Results for Predicting Whether the Number of Attendance flags Raised for College-Level Students Impacts Persistence

Step	Variable Entered	B	Wald	Significance	Exp(B)	95% C.I. for Exp(B)	
						Lower	*Upper*
1	Number of *Attendance* flags Raised	-.070	16.657	.000	.933	.902	.964
	Constant	.345	3,078.740	.000	1.412		

Developmental English. Results of the logistic regression indicated that the predictor model was not statistically significant. Table 14 presents the regression coefficients (B), the Wald statistics, significance level, odds ratio [Exp(B)], and the 95 percent confidence intervals (CI) for odds ratios (OR) for the predictor.

Table 14.

Logistic Regression Results for Predicting Whether the Number of Attendance flags Raised for Developmental English Students Impacts Persistence

Step	Variable Entered	B	Wald	Significance	Exp(B)	95% C.I. for Exp(B)	
						Lower	*Upper*
1	Number of *Attendance* flags Raised	.123	2.333	.127	1.131	.966	1.326
	Constant	-.128	17.543	.000	.879		

Developmental mathematics. The results of the logistic analysis indicated that the predictor model provides a statistically significant and positive impact on persistence over the constant model. $X^2(1, N = 1{,}707) = 408.068, p < .001$. The Nagelkerke R square indicates that the model does not account for the total variance (null value). This suggests that the predictor variable (number of *Attendance* flags raised) does not discriminate between those who persisted and those who did not. Prediction success was high for those that did not persist (93.7 percent) and for those that did persist (71.0 percent). The beta for the independent variable was positive suggesting a positive impact on persistence. Further, the expected beta (odds ratio) suggests that for every one *Attendance* flag raised (up to three), a student is nearly 18 times more likely to persist. Table 15 presents the regression coefficients (B), the Wald statistics, significance level, odds ratio [Exp(B)], and the 95 percent confidence intervals (CI) for odds ratios (OR) for the predictor.

Table 15.

Logistic Regression Results for Predicting Whether the Number of Attendance flags Raised for Developmental Mathematics Students Impacts Persistence

Step	Variable Entered	B	Wald	Significance	Exp(B)	95% C.I. for Exp(B)	
						Lower	*Upper*
1	Number of *Attendance* flags Raised	2.879	294.045	.000	17.796	12.806	24.730
	Constant	-2.771	621.845	.000	.063		

Research Question 3

Research question three examined the impact the number of *In Danger of Failing* flags had on student persistence to the next semester. Specifically, this impact was evaluated for students enrolled in college-level courses, developmental English, and developmental mathematics.

College-level. Results of the logistic analysis indicated that the predictor model was not statistically significant. Table 16 presents the regression coefficients (B), the Wald statistics, significance level, odds ratio [Exp(B)], and the 95 percent confidence intervals (CI) for odds ratios (OR) for the predictor.

Table 16.

Logistic Regression Results for Predicting Whether the Number of In Danger of Failing Flags Raised for College-Level Students Impacts Persistence

Step	Variable Entered	B	Wald	Significance	Exp(B)	95% C.I. for Exp(B)	
						Lower	*Upper*
1	Number of *In Danger of Failing* Flags Raised	.013	.695	.404	1.013	.983	1.045
	Constant	.351	3,188.985	.000	1.421		

Developmental English. Results of the logistic analysis indicated that the predictor model was not statistically significant. Table 17 presents the regression coefficients (B), the Wald statistics, significance level, odds ratio [Exp(B)], and the 95 percent confidence intervals (CI) for odds ratios (OR) for the predictor.

Table 17.

Logistic Regression Results for Predicting Whether the Number of In Danger of Failing flags Raised for Developmental English Students Impacts Persistence

Step	Variable Entered	B	Wald	Significance	Exp(B)	95% C.I. for Exp(B)	
						Lower	*Upper*
1	Number of *Attendance* flags Raised	.073	.718	.397	1.076	.909	1.273
	Constant	-.129	17.684	.000	.879		

Developmental mathematics. Results of the binary logistic regression analysis provided a statistically significant model, $X^2(1, N = 1{,}858) = 772.398$, $p < .001$. The Nagelkerke R square indicates that the model accounted for 54 percent of the total variance, suggesting a moderate relationship between the predictor variable (number of *In Danger of Failing* flags raised) and prediction of those who persisted and those who did not. Prediction success was high for those that did not persist (92.7 percent) and for those that did persist (81.5 percent). The beta was positive suggesting a positive impact on persistence. Further, the expected beta (odds ratio) suggests that for every one *Attendance* flag raised in a developmental mathematics course (up to three), a student is nearly 40 times more likely to persist. Table 18 presents the regression coefficients (B), the Wald statistics, significance level, odds ratio [Exp(B)], and the 95 percent confidence intervals (CI) for odds ratios (OR) for the predictor.

Table 18.

Logistic Regression Results for Predicting Whether the Number of In Danger of Failing Flags Raised for Developmental Mathematics Students Impacts Persistence

Step	Variable Entered	B	Wald	Significance	Exp(B)	95% C.I. for Exp(B)	
						Lower	*Upper*
1	Number of *In Danger of Failing* Flags Raised	3.613	521.616	.000	37.077	27.192	50.554
	Constant	-2.842	610.657	.000	.058		

Research Question 4

Research question four examined the impact the number of flags of any kind had on student persistence to the next semester. Specifically, this impact was evaluated for students enrolled in developmental English and developmental mathematics.

Developmental English. Results of the analysis indicated a statistically significant and positive impact on persistence over the constant model. $X^2(1, N = 5{,}387) = 20.117, p < .001$. The Nagelkerke R square indicates that the model accounted for .5 percent of the total variance. This suggests that the predictor variable (number of flags raised) has a very weak relationship with prediction of persistence. The beta was positive suggesting a positive impact on persistence, with the expected beta (odds ratio) at1.153. This suggests that for every one flag raised (up to five), a student is 1.153 times more likely to persist. Prediction success was high (82.7 percent) for those that did not persist, but only 26 percent for those that did persist. Table 19 presents the regression coefficients (B), the Wald statistics, significance level, odds ratio [Exp(B)], and the 95 percent confidence intervals (CI) for odds ratios (OR) for the predictor.

Table 19.

Logistic Regression Results for Predicting Whether the Number of Flags Raised for Developmental English Students Impacts Persistence

Step	Variable Entered	B	Wald	Significance	Exp(B)	95% C.I. for Exp(B)	
						Lower	*Upper*
1	Number of Flags Raised	.142	19.738	.000	1.153	1.083	1.227
	Constant	-.077	6.703	.010	.926		

Developmental mathematics. Results of the analysis indicated a statistically significant model, $X^2(1, N = 2{,}513) = 905.238$, $p < .001$. The Nagelkerke R square indicates that the model accounted for 41.6 percent of the total variance, suggesting a moderate relationship between the predictor variable and prediction of persistence. Prediction success was high (92.2 percent) for those that did not persist, and 43.4 percent for those that did persist. The beta for the independent variable was positive suggesting a positive impact on persistence. Further, the expected beta (odds ratio) indicates that for every one flag raised (up to five), a student is 4.5 times more likely to persist. Table 20 presents the regression coefficients (B), the Wald statistics, significance level, odds ratio [Exp(B)], and the 95 percent confidence intervals (CI) for odds ratios (OR) for the predictor.

Table 20.

Logistic Regression Results for Predicting Whether the Number of Flags Raised for Developmental Mathematics Students Impacts Persistence

Step	Variable Entered	B	Wald	Significance	Exp(B)	95% C.I. for Exp(B)	
						Lower	*Upper*
1	Number of Flags Raised	1.520	544.160	.000	4.570	4.022	5.193
	Constant	-1.755	649.005	.000	.173		

CHAPTER 5
DISCUSSION

American colleges and universities continue a decades-long challenge to improve student retention rates (Bailey et al., 2015; Braxton et al., 2014; Nodine et al., 2011; Tinto, 1993, 2007, 2012). Despite numerous theories and strategies designed to explain and increase retention rates, less than 60 percent of full-time, first-time students were retained between Fall 2013 and Spring 2014 (NSC, 2015a). Within two-year colleges, less than half of students were retained in the same period (NSC, 2015a).

In the midst of this ongoing challenge, community colleges are now facing a dual mission, which calls for a continued focus on access while also emphasizing student completion. The emphasis on completion has driven a dramatic increase in the presence of performance-based funding, which directly ties state funding to student outcomes (AASCU, 2014; Bailey et al., 2015). Accordingly, institutional leaders and practitioners often become consumers of a booming retention industry that offers a plethora of products and strategies promising to improve student retention and completion rates.

A notable strategy touted within the retention industry and widely implemented across higher education institutions is early alert systems (Barefoot, 2004) - a systemic method used to identify students demonstrating at-risk behaviors and prompt interventions to prevent attrition (Tampke, 2013). These systems are predicated on the notion that the earlier a student is alerted to at-risk behaviors and subsequently provided an intervention to address the behaviors, the more likely they are to change their trajectory, satisfactorily complete the course, and re-enroll (Cohen et al., 2013; Tinto 2012).

The Virginia Community College System (VCCS) launched an early alert system in 2013 at each of its 23 community colleges. While each college had autonomy on how they provide interventions in response to flags, they were all required to 1) use the early alert system, 2) use the same flags, and 3) prompt faculty to engage with the system at common, scheduled points in the 16-week semester. This systemic and shared approach provided a rich landscape for research due to the common implementation across a diverse array of colleges and a high volume of students.

Despite widespread use of early alert systems, however, there is little empirical evidence that speaks to their efficacy. The limited research that has been conducted has largely taken place in four-year institutions (Brothen et al., 2003; Cai et al., 2015; Hansen et al., 2002; Hudson, 2006; Tampke, 2013) and when in community colleges, almost exclusively focused on developmental education students (Green, 2015; Simpson, 2014; Wladis et al., 2014). Furthermore, previous studies have produced mixed results with some indicating a positive impact (Cai et al., 2015; Hudson, 2006; Tampke, 2013; Wladis et al., 2014) and others demonstrating little to no impact (Brothen et al., 2003; Hansen et al., 2002; Simpson, 2014). The limited research and inconclusive nature of previous findings created a need for additional research to determine if and how early alert systems are working in community colleges.

Purpose Statement and Research Questions

The purpose of this study was to examine the relationship between the use of an early alert system and persistence for students taking developmental education courses and students taking college-level courses in the Virginia Community College System.

This study was guided by the following research questions:

1. What impact does the number of *Academic* flags have on student persistence to the next semester?

1a. What impact does the number of *Academic* flags raised in a college-level course have on student persistence to the next semester?

1b. What impact does the number of *Academic* flags raised in a developmental English course have on student persistence to the next semester?

1c. What impact does the number of *Academic* flags raised in a developmental mathematics course have on student persistence to the next semester?

2. What impact does the number of *Attendance* flags raised have on student persistence to the next semester?

2a. What impact does the number of *Attendance* flags raised in a college-level course have on student persistence to the next semester?

2b. What impact does the number of *Attendance* flags raised in a developmental English course have on student persistence to the next semester?

2c. What impact does the number of *Attendance* flags raised in a developmental mathematics course have on student persistence to the next semester?

3. What impact does the number of *In Danger of Failing* flags raised have on student persistence to the next semester?

3a. What impact does the number of *In Danger of Failing* flags raised in a college-level course have on student persistence to the next semester?

3b. What impact does the number of *In Danger of Failing* flags raised in a developmental English course have on student persistence to the next semester?

3c. What impact does the number of *In Danger of Failing* flags raised in a developmental mathematics course have on student persistence to the next semester?

4. What impact does the number of flags raised have on developmental education student persistence to the next semester?

   4a. What impact does the number of flags raised have on developmental mathematics student persistence to the next semester?

   4b. What impact does the number of flags raised have on developmental English student persistence to the next semester?

Summary of Methodology

The above research questions were examined using a quantitative, quasi-experimental, non-randomized research design with a matched-control group. All data were collected from the VCCS Office of Institutional Research and Effectiveness (OIRE) in January 2017 and were comprised entirely of existent data. Student names were removed and assigned a unique identifier to protect student anonymity. Although the VCCS OIRE provided all data to the researcher, there were two primary sources of data for persistence – the National Student Clearinghouse provided information on students that successfully transferred to another college or university and VCCS records provided data on students that graduated and those that re-enrolled in Spring 2016. All data on flags raised were derived from the VCCS early alert system and all student demographic and enrollment data were collected from the VCCS student information system.

The non-randomized design reflects students' interaction, or lack thereof, with the early alert system in the Fall 2015 semester. Students were placed into the treatment group if they received an early warning flag and students not receiving a flag were placed in the control group. The treatment and control groups were limited to students who were program-placed and enrolled in a sixteen week course during Fall 2015.

The validity of the study's results were then enhanced by creating matched-control groups using the following four binary matched factors: Pell-recipient status (yes/no), first-generation (yes/no), full- or part-time status, and age (24 years or less; 25 years or greater). Creating the control groups on these matched factors mimicked random assignment, reduced bias, and was complimentary to regression-based data analysis (Stuart & Rubin, 2008). Each student was then categorized into one of sixteen strata, representing each possible combination of the four matched factors to ensure that students within each treatment and control group were represented in each strata. To further examine the strength of the matched control groups, a chi square analysis was conducted in order to determine if the groups were alike on variables not included in the strata – gender and race. A preponderance of the analysis of the strata were alike for developmental English and developmental mathematics students, further demonstrating the similarity of the treatment and control groups. To confirm the control group for college-level students, additional analysis was conducted. Two binary logistic regression models were run – one including race and gender and one not including them. When comparing results, race and gender presented negligible differences, further adding to the strength of the control group.

Once all data were prepared and the treatment and matched control groups confirmed, data analysis was conducted using binary logistic regression. This analytical method was selected based on the binary outcome in each research question (student persistence or not) and the desire to predict an outcome based on the variables (Field, 2009). The seven statistical assumptions associated with binary logistic regressions were tested and confirmed as noted in Chapter Three.

Summary of Findings

Findings indicate that the type of course enrollment is a better predictor of the impact of the early alert system than flag type. Specifically, the early alert system had the most significant and positive impact on students enrolled in developmental mathematics courses, regardless of flag type. The impact on developmental English students was positive, yet mild, while students enrolled in college-level courses experienced mixed results. Further detail on the impact by flag type and course enrollment is provided below. In addition, Table 21 summarizes the odds ratio by flag type and course enrollment. The odds ratio is “an indicator of the change in odds resulting from a unit change in the predictor in logistic regression.” (Field, 2009, p. 874). In other words, for every additional flag (up to the plausible high noted in Table 8), a student is more or less likely to persist by the odds ratio. For example, for every *Academic* flag raised (up to 3), a developmental English student is 1.532 times more likely to persist. Conversely, for every *Attendance* flag raised (up to 3), a student in a college-level course is 1.067 times more likely *not* to persist.

Table 21.

Summary: Odds Ratio by Flag Type and Course Enrollment

Flag Type	Developmental English	Developmental Mathematics	College-Level
Academic	1.532	19.033	1.221
Attendance	-	17.796	.933
In Danger of Failing	-	37.077	-
All	1.153	4.570	N/A

- *indicates the results of the analysis were not statistically significant*

Results by course enrollment. Findings suggest that the efficacy of the early alert system varies widely across the type of course enrollment (college-level, developmental English, or developmental mathematics). Developmental mathematics students experience a much stronger and more positive impact from the early alert system than students in developmental English or college-level courses.

College-level. Students enrolled in college-level courses had both a positive and negative impact, depending on the flag type. For every *Academic* flag received (up to four), a student is 1.2 times more likely to persist. *Attendance* flags, however, presented a negative impact. For every *Attendance* flag raised (up to four), a student is 1.07 times less likely to persist. The impact of the *In Danger of Failing* flag on college-level students was not statistically significant.

Developmental English. Students enrolled in developmental English are 1.5 times more likely to persist for every *Academic* flag raised, up to three flags. The impact of the *Attendance* and *In Danger of Failing* flags were not statistically significant. When evaluating the impact on a developmental English student, regardless of flag type, findings indicate a student is 1.15 times more likely to persist for every flag raised, up to five flags.

Developmental mathematics. Lastly, results indicate that students enrolled in developmental mathematics courses experience the greatest impact from the early alert system compared to developmental English and college-level student enrollments. For every *Academic* or *Attendance* flag raised (up to three for either), a student is nearly 20 times more likely to persist. The *In Danger of Failing* flag has an even greater impact with students being 37 times more likely to persist per flag, up to three flags. When evaluating the impact of any flag being raised on a developmental mathematics students, results suggest the student is 4.5 times more likely to persist, up to five flags.

Results by flag type. Results of the impact on student persistence, by flag type, were less dramatic. The impact of the *Academic* flag was positive across all course enrollment types examined, but the degree of impact varied widely, with odds ratios ranging from 1.2 to 19. The *Attendance* flag produced a positive odds ratio (17.8) for developmental mathematics students, but a negative impact (.9) for college-level. The result for the *Attendance* flag for developmental English students was not statistically significant. The *In Danger of Failing* flag had a very positive impact on developmental mathematics students (37 odds ratio), but was not statistically significant for students in developmental English and college-level courses, thereby making it impossible to establish a trend of impact across course enrollment types. In sum, findings suggest that flag type, across student populations, is not an effective predictor of impact on persistence.

Findings Related to the Literature

Findings from this study add to a limited body of empirical research and knowledge about the efficacy of early alert systems. A majority of previous research focused on four-year institutions, creating a gap in knowledge about the impact of early alert systems in a community college setting. Further, this study offers greater comparison among flag type and type of course enrollment than previous studies. In some cases, it supports a general positive outcome associated with use of early alert systems (Bourdon & Carducci, 2002). In many cases, however, it provides clarity to the literature by delineating developmental mathematics, developmental English, and college-level students as well as flag type.

Impact on students enrolled in developmental education courses. A majority (75 percent) of community college students arrive academically under-prepared (Goldrick-Rab & Cook, 2011). This is an undeniable challenge for community college leaders as only one quarter of community college students that require developmental education earn a certificate or degree within eight years (Bailey & Cho, 2010). In an attempt to improve retention rates, the VCCS launched an early alert system in 2013 for use in developmental education and gateway courses and optional use in college-level courses. Results support previously held beliefs that early alert systems generally have a positive impact on developmental education students (Hudson, 2006). Findings from this study, however, provide greater clarification on the impact by type of developmental education student (English or mathematics).

Developmental mathematics. This study shows early alert systems have a clear and positive impact on developmental mathematics students, across all flag types. In 2014, Wladis et al. found developmental mathematics students experienced 50% higher passing rates after implementation of an early alert system. Notably, however, this study included a considerable confounding variable – the redesign of the developmental mathematics curriculum and intentional engagement of faculty. Thus, the study does not delineate the impact of the early alert from the redesign.

Similarly, Cai et al. (2015) found positive results for mathematics students in a four-year setting, but they were intentionally examining the likelihood that the early alert system encouraged students to use the university tutoring center and subsequent academic performance. While results were positive, it is unclear how much of the academic success is attributed to the early alert system versus the services provided in the tutoring center.

Thus, this study supports the general positive outcomes of previous studies and provides further clarification into direct impact of the early alert system while minimizing confounding variables. It also shows that developmental mathematics students are nearly 20 times more likely to persist for every *Academic* or *Attendance* flag raised (up to three flags), with an even greater impact for the *In Danger of Failing* flag.

Developmental English. Results of this study contradict previous studies focused on developmental English students. While earlier research shows a positive and statistically significant relationship between course outcomes (grades) and the use of an early alert system, results were not statistically significant results pertaining to persistence (Green, 2015). The current study, however, suggests that the early alert system had a positive and statistically significant impact on developmental English student persistence in certain conditions. Specifically, developmental English students are 1.5 times more likely to persist for every *Academic* flag raised (up to three flags). Less impactful, but still statistically significant, these students are 1.1 times more likely to persist for every flag raised, regardless of flag-type, up to five flags. Like in Green (2015), however, some results were not statistically significant – the impact associated with use of *Attendance* and *In Danger of Failing* flags. Generally speaking, it appears that early alert systems do have a positive impact on developmental English students, but the impact is not as great as it is with their counterparts in developmental mathematics.

Impact on students enrolled in college-level courses. Previous research on the impact of early alert systems on students in college-level courses has been almost exclusively focused in four-year colleges and universities (Brothen et al., 2003; Cai et al., 2015; Hansen et al., 2002; Tampke, 2013). The current study, therefore, builds upon that research and provides further insight into the impact on a different student population – those enrolled in college-level classes in a community college setting. Like previous research in four-year institutions, the current study produced mixed results when evaluating the impact on student persistence. For example, prior research has produced modest, but positive results when evaluating the student outcomes (i.e., grades and re-enrollment) for graduate and undergraduate students enrolled at a university (Tampke, 2013). A modest and positive result was also found in the current study for those receiving *Academic* flags. The impact of the *Attendance* flag, was modest and negative, however, which contradicts Tampke's (2013) findings.

On the other hand, it has been shown that the impact of early alert systems are not statistically significant when evaluating students in a general psychology course (Brothen et al., 2003; Hansen et al., 2002). This is consistent when examining the impact of *In Danger of Failing* flags for those enrolled in college-level courses in a community college setting. In sum, this study aligns with previous studies that demonstrated minimal and varied results for students enrolled in college-level courses.

Impact of flag type. While early alert systems have generally been associated with positive effects (Bourdon & Carducci., 2002), previous research has not addressed the impact of various types of flags or alerts, thereby creating a knowledge gap addressed by this study. Results, however, suggest that flag type has less predictive value on persistence than course enrollment. *Academic* flags were consistently associated with a positive impact on persistence. The *Attendance* flag produced mixed results within this study, while effects of an early alert system on absenteeism and retention were previously examined and produced positive results (Hudson, 2006). *In Danger of Failing* flags produced both positive results as well as results that were not statistically significant. In sum, *Academic* flags appear to have the greatest impact on student persistence, but flag type is not a significant determinant in efficacy of the system.

Implications for Policy and Practice

Results of this study have direct and practical utility for community college leaders and practitioners. First, findings support institutional leaders in developing policy that targets fiscal and human resources in areas where early alert systems have the greatest impact. Specifically, findings indicate that course enrollment is a critical element when predicting the efficacy of an early alert system and should therefore be considered when allocating resources. Second, the data also speak to the potential benefits of an early alert system and how it might enhance a comprehensive retention plan. Lastly, practitioners now have greater insight into the effect of various flag types and the impact of raising multiple flags.

Targeting early alert resources based on course enrollment. Community college leaders and policymakers have long focused attention on improving academic outcomes and retention of students enrolled in developmental education. This focus is driven by a plethora of data showing that the chance of student retention decreases as the need for academic remediation increases (Bailey & Smith Jaggars, 2016; Goldrick-Rab & Cook, 2011). Results of this study suggest that policymakers are, indeed, wise to concentrate their retention efforts on students in specific courses, such as developmental education.

Under pressure from the aforementioned completion agenda, community colleges across the nation have reformed the curriculum, delivery, and support services that comprise and surround developmental education (Bailey & Smith Jaggars, 2016). In many states, including Virginia, such reforms included the addition of an early alert system (Edgecombe, 2016). Reforms, however, have taken a variety of shapes, including modularization of courses, co-requisites with college-level courses, learning communities, and more (Bailey & Smith Jaggars, 2016). In addition to curriculum and pedagogical reforms, institutional leaders have often embraced the notion of providing more comprehensive support services, such as enhanced academic advising, career exploration, and tutoring. Early alert systems serve as an integral piece of many redesigns – a bridge between the reformed curriculum and enhanced support services. In other words, as students begin to show signs of distress in the coursework, the early alert system is intended to guide them to the necessary interventions, which are typically provided through support services. The results of this study suggest that this is an effective practice with developmental mathematics courses. The impact of this practice, however, is not as significant in developmental English and should be reconsidered for college-level courses.

Increase use by developmental mathematics faculty. Fifty-nine percent of community college students require developmental mathematics, with only 33 percent of those eventually moving on to college-level math (Bailey, Jeong, & Cho, 2010). Findings of this study indicate that use of an early alert system is an effective means of improving student persistence with developmental mathematics students. Thus, institutional leaders are advised to develop policy or procedure requiring integration of the early alert system by developmental mathematics faculty.

Similarly, given the significant and positive impact of the early alert system with developmental mathematics students, policymakers may consider how use of the early alert system can be further integrated into various delivery formats. While this study focused on the impact of the early alert system within 16-week courses, a number of VCCS colleges also offer shorter, modularized courses that are designed to expedite the process of moving to college-level mathematics by targeting and addressing student-specific deficiencies (Edgecombe, 2016). Further exploration of the impact of the early alert system in the modularized class environment is warranted, so policies and procedures can be customized to maximize impact based upon course type. In sum, this study suggests early alert systems should be fully embraced by developmental mathematics faculty, and policymakers would be wise to continue an investment in resources for this student population.

Target academic concerns in developmental English. This study suggests developmental English students experience a positive effect from *Academic* flags, while the impact of the *Attendance* and *In Danger of Failing* flags are not statistically significant. Thus, it is recommended that developmental English faculty target their time and attention within the early alert system on academic concerns. When students demonstrate excessive absenteeism or are likely to fail the course, faculty and staff resources may be best focused on retention methods outside of the early alert system. Further, given the very positive impact of the early alert system with developmental mathematics, data could suggest that institutional leaders need to review the business model(s) and intervention methods used in those courses to determine potential applicability within developmental English courses.

Modify or discontinue use in college-level courses. Prior research on the efficacy of early alert systems in community colleges has been exclusively focused on developmental education students (Green, 2015; Simpson, 2014; Wladis et al.,2014), thereby creating a gap in knowledge pertaining to the impact on students enrolled in college-level courses. The findings of this study, however, begin to shed light onto this important student population and how practitioners might adjust their practices with the early alert system. While results were both positive and negative, depending on the flag type, the impacts were minimal, suggesting that a large investment of budget on college-level faculty and staff time – using current practices – may not provide the anticipated return.

Given the demonstrated success with developmental mathematics students, however, findings suggest an untapped potential within college-level courses as well. Notably, the early alert system in the VCCS was first launched within developmental education and gateway courses (e.g., entry college-level math and English courses), gaining early use and buy-in. Subsequently, the system was opened for optional use in the remaining college-level courses. Use across college-level disciplines varies greatly. Thus, institutions may benefit from examining the impact of early alert in various college-level disciplines and target resources accordingly. For example, if college-level mathematics presents a greater impact than college-level English, resources may be targeted to that discipline, regardless of course level.

Alternatively, if further exploration and adaptation of practices are not embraced, the data suggest institutional leaders should discontinue use of the early alert system in college-level courses. However, because the institution already invests in the early alert system and data show a significant benefit with specific student populations, there is an opportunity to maximize the benefit for those enrolled in college-level courses, rather than simply discontinue use. In other words, because funds are being allocated to this service, college leaders will maximize efficiency of those funds by finding effective ways to use the system with college-level students as well.

Employing early alert systems in a comprehensive retention plan. As noted above, results of this study indicate a positive impact of the early alert system with certain student populations. It is worth noting, however, that even where student persistence is positively impacted, some student attrition still exists. This suggests that early alert systems can be an important component of a more comprehensive retention strategy, but are not a "silver bullet" to address completion goals. Given the completion agenda and a shift towards performance-based funding, community colleges nationwide are developing comprehensive retention plans that attempt to integrate a variety of strategies and initiatives.

For example, many community colleges are embracing the concept of structured pathways to efficiently guide students through the academic experience (Bailey et al., 2015). Within a community college setting, pathways often begin with the enrollment process and then quickly move into developmental education. Within a structured pathway model, early alert systems are employed as a method of identifying students requiring additional assistance in order to successfully navigate the pathway to graduation. Results from this study indicate that all students do not benefit equally from the early alert system. Thus, it is recommended that institutional leaders develop a standard early alert business model that specifically addresses when, how, and where in a pathway the early alert system will be used. As a student navigates a pathway to college completion, the data could indicate, for example, that the early alert system could have a positive impact on the required sequence of mathematics courses. Thus, as institutional leaders and practitioners design structured pathways and a standard business model to support student advancement, findings from this study could suggest that use of an early alert system should be included in prescribed environments.

In addition, given the positive impact of the early alert system on student persistence, data could suggest that increased use with particular populations would positively influence college completion rates. Thus, institutional leaders are encouraged to find ways to increase ease of access and use of the system for faculty and staff serving the identified student populations. For example, exploration into how the early alert system can be seamlessly integrated into a learning management system and other electronic resources used frequently in the course may influence utilization of the system. Again, a standard business model and policy or procedure integrating use of the system into faculty expectations may effectively contribute to institutional completion goals.

Refining flag types and dosage. Finally, this study provides insight into how institutional leaders could refine the flag types within the system as well as how the number of flags raised contributes to improved student persistence. Data show the impact of the flag type varies by type of course enrollment. Thus, institutional leaders should explore the feasibility of customizing faculty access to flag types, depending on the course. For example, data suggest that developmental mathematics faculty should have access to all flag-types given the significant and positive impact with all flags. In college-level courses, however, the *Attendance* flags had a negative impact, therefore suggesting they should be removed as an option within those courses. Similarly, in areas where that impact was not statistically significant (e.g., *In Danger of Failing* flags for developmental English students), students may not be harmed by a faculty member raising a particular flag type, but college leaders would be best served to direct student support staff time to flags of greatest impact (*Academic* flags). Such customizations and refinement to how and when flag types are used within the system may result in greater impact and efficiencies derived from the system.

Similarly, findings indicate a value in raising more than one flag when a student problem persists or reappears. Table 8 describes the plausible high number of flags used in determining the impact described in Chapter Four. In other words, for every flag raised, up to the number noted in Table 8, the positive or negative impact is felt in student persistence. Thus, institutional leaders are advised to inform faculty about the benefit of their diligence in raising flags, up the maximum noted in the table. Perhaps more importantly, however, is establishing a business process for student support staff providing the interventions. Because student support staff have a comprehensive view of all flags raised on students (which faculty are not privy to), staff efforts should be targeted on students with multiple flags, up the maximum noted in the table. For example, if a developmental English student has two *Academic* flags raised, the student is likely to be positively influenced by the early alert intervention. If, however, that student exceeds the plausible high (four or more flags, in this case), the staff member's time may not produce the expected impact. Thus, the findings of this study suggest that institutional leaders may provide greater support for student persistence by developing or refining business models detailing the impact of flag dosage and targeting faculty and student support staff time accordingly.

Recommendations for Future Research

This study's findings illuminate opportunities for further investigation in several areas that would provide deeper understanding of the utility and efficacy of early alert systems. First, as noted in Chapter Three, this study contains limitations that could be addressed in future studies. One of the primary limitations of the current study is the lack of random assignment. Given the limited impact in developmental English and college-level courses, as demonstrated by this study, the ethical concerns of not providing this service to students is minimized. Thus, for these populations, there would be value in randomly generating a control and treatment group and rerunning the analysis. When using random assignment, it would be advisable to ensure that treatment and control groups are equally represented for each faculty member included. This would help to control for the subjectivity involved in when and how often faculty raise flags. Alternatively, specific direction could be provided to faculty raising flags on the treatment group of particular thresholds that warrant flags. Lastly, this study could be enhanced by gathering data for a pre-test that is indicative of previous academic performance, such as high school grade point average, in order to further ensure like control and treatment groups.

Similarly, this study was intentionally limited to the evaluation of 16-week courses and evaluating persistence from fall to spring. Nonetheless, there are a considerable amount of modularized courses offered in non-traditional schedules (not 16-week courses) that warrant exploration. Likewise, there would be additional value in examining if the impact identified in this study continues when examining college-level mathematics and English courses.

In addition to addressing the limitations of this study, there are ample opportunities to conduct studies that would build upon and complement these findings. For example, while the key feature of an early alert system is flags – or electronic warnings indicative of at-risk behavior – an additional feature frequently used with the VCCS is kudos. Kudos are electronic messages of encouragement and recognition for progress or a job well done. Several learning theories suggest that the reinforcement provided by kudos may have positive impact on student performance and persistence. Thus, there is ample opportunity for this study to be replicated and supplanting the flags with the three types of kudos used the in the VCCS early alert system.

Furthermore, due to the various forms of early alert systems implemented across the nation, there would be value in conducting a similar study in another state using a different form of early alert to determine if the strength of an early alert system – regardless of brand – has a similar impact on developmental mathematics students.

Although the current study identifies students enrolled in developmental English, developmental mathematics, and college-level courses, it would be beneficial to examine the impact of early alert warnings for other student categories (i.e., first-generation college students, veterans, financial aid recipients, underrepresented student populations, etc.). Deeper understanding of which students are most likely to benefit from early alert practices would allow institutional leaders and policymakers to better target limited resources.

Further, due to consistency of the tool across 23 colleges, but inconsistency in implementation methods, the VCCS is an environment ripe to study and compare implementation practices - quantitatively and qualitatively. Further research is warranted to examine how faculty and staff respond to various flags and student populations. Additional research regarding the amount of time between a flag being raised and when the issue is addressed is also required. Moreover, there would be value in examining how the early alert system perceived by faculty, staff, and students as well as the perceived and measurable benefits beyond student persistence. Future research into each of these areas is warranted and would further contribute to the literature and effective use of early alert systems.

Lastly, a full return-on-investment analysis for individual colleges - or the VCCS system as a whole - would be valuable. The cost to the system and each individual college exists not only in payment to the vendor for use of the early alert system, but also in the investment of faculty and staff time and resources. The possible fiscal benefits include increased tuition revenue associated with student persistence, a reduction in Return to Title IV funds in financial aid (due to higher course pass rates), and greater revenue in state performance-based funding. A thorough cost/benefit analysis, in addition to this study and the possible studies noted above, would provide institutional leaders with a wealth of knowledge to determine if the fiscal and academic benefits of the early alert system outweigh the costs.

Conclusion

Student retention has been at the forefront of the minds of higher education leaders and policymakers for decades. It is widely understood that institutions of higher education play a critical role in student retention and the benefits of effectively doing so positively impact the student, the institution, and society broadly. With an evolving mission and a dramatic shift towards performance-based funding, there is a new and very pronounced fiscal impact associated with student outcomes. Institutional benefits of retention are no longer simply reflected in continued tuition dollars, but also frequently impact state funding as well. This heightened fiscal impact, along with the dual access and completion mission enforced at local, state, and federal levels, continues to shine a spotlight on the issue of student retention and completion.

The significance and urgency of retention as an issue in higher education has led institutions to invest in solutions that promise to positively impact student completion rates. Early alert systems, a cornerstone of a vibrant retention industry, have been implemented in a majority of institutions across the country (Barefoot, 2004). This study found that early alert systems are, indeed, an effective method to enhance student persistence in certain conditions. Although beneficial, data indicates that the early alert system is not equally effective among all student populations. Results suggest that college leaders would benefit from targeting their limited resources to those populations (e.g., developmental mathematics students) that receive the maximum benefit. Data also suggest that efforts to refine practices with developmental English and college-level students may allow the college to further capitalize on their investment in the early alert system. Further, as institutions develop and refine comprehensive retention plans, results of this study demonstrate that early alert systems can be an effective strategy in reaching increased completion rates. Data suggest, however, that early alert systems are not providing the anticipated return for all populations and therefore should be complemented by alternative retention strategies. Lastly, this study produced detailed information on the value of flag types and the benefit of persistence in raising flags as student distress continues. In sum, early alert systems have demonstrated a notable benefit in defined community college settings and have the potential to be a valuable component of a comprehensive completion agenda.

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APPENDIX A

Braxton et al. (2014) 13 Propositions of the Interactionalist Theory of Student Departure

1. Student entry characteristics affect the level of initial commitment to the institution.
2. Student entry characteristics affect the level of initial commitment to the goal of graduation from college.
3. Student entry characteristics directly affect the student's likelihood of persistence in college.
4. Initial commitment to the goal of graduation from college affects the level of academic integration.
5. Initial commitment to the goal of graduation from college affects the level of social integration.
6. Initial commitment to the institution affects the level of social integration.
7. Initial commitment to the institution affects the level of academic integration.
8. The greater the degree of academic integration, the greater the level of subsequent commitment to the goal of graduation from college.
9. The greater the degree of social integration, the greater the level of subsequent commitment to the institution.
10. The initial level of institutional commitment affects the subsequent level of institutional commitment.
11. The initial level of commitment to the goal of graduation from college affects the subsequent level of commitment to the goal of college graduation.
12. The greater the level of subsequent commitment to the goal of graduation from college, the greater the likelihood of student persistence in college.

13. The greater the level of subsequent commitment to the institution, the greater the likelihood of student persistence in college.

APPENDIX B

Braxton et al. (2014) Eight Propositions for Residential Colleges and Universities

1. The greater the student's belief that they have the ability to pay for the cost of attending the chosen college or university, the greater the student's degree of social integration.
2. The more a student perceives that the institution is committed to the welfare of its students, the greater the student's level of social integration.
3. The more a student perceives the potential for community on campus, the greater the students' level of social integration.
4. The more a student perceives that the institution exhibits institutional integrity, the greater the student's level of social integration.
5. The greater the student's use of proactive adjustments strategies, the greater the student's level of social integration.
6. The greater the level of psychological energy that a student invests in various social interactions at their college or university, the greater the student's degree of social integration.
7. The greater the student's degree of social integration, the greater their level of subsequent commitment to the college or university
8. The greater the level of subsequent commitment to the institution, the more likely the student persists in college.

APPENDIX C

Braxton et al. (2014) 11 Propositions for Commuter Colleges

1. As parental educational level increases, the likelihood of student persistence in a commuter college or university decreases.
2. The higher the student's level of motivation to graduate from college, the greater their likelihood of persisting in a commuter college or university.
3. The lower the costs of college attendance incurred by the student, the greater their likelihood of persisting in a commuter college or university.
4. The greater the support the student receives from significant others for their college attendance, the greater their likelihood of persistence in a commuter college or university
5. The greater the student's need for social affiliation, the lower their likelihood of persistence in a commuter college or university.
6. The more a student perceives that their college or university is committed to the welfare of is students, the greater the student's degree of academic and intellectual development.
7. The more a student perceives that their college university exhibits institutional integrity, the greater the student's degree of academic and intellectual development.
8. The more a student perceives that their college or university is committed to the welfare of its students, the greater the student's degree of subsequent commitment to their college or university.
9. The more a student perceives that their college or university exhibits institutional integrity, the greater the student's degree of subsequent commitment to their college or university.

10. The greater the degree of academic an intellectual development perceived by a student, the greater the student's degree of subsequent commitment to a commuter college or university.
11. The greater the student's degree of subsequent institutional commitment, the greater the likelihood of the student's persistence in a commuter college or university.

APPENDIX D

OLD DOMINION UNIVERSITY

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DATE:	December 21, 2016
TO:	Mitchell Williams
FROM:	Old Dominion University Education Human Subjects Review Committee
PROJECT TITLE:	[997275-1] Early Alert: An Analysis of the Impact on Student Persistence in Community Colleges
REFERENCE #:	
SUBMISSION TYPE:	New Project
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	December 21, 2016
REVIEW CATEGORY:	Exemption category # *[6.4]*

Thank you for your submission of New Project materials for this project. The Old Dominion University Education Human Subjects Review Committee has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

We will retain a copy of this correspondence within our records.

If you have any questions, please contact Petros Katsioloudis at (757) 683-5323 or pkatsiol@odu.edu. Please include your project title and reference number in all correspondence with this committee.

This letter has been electronically signed in accordance with all applicable regulations, and a copy is retained within Old Dominion University Education Human Subjects Review Committee's records.

APPENDIX E

Table 22.

Research Question 1-4: Control Group Characteristics (Mean Scores)

Characteristic	Control Groups		
	College-Level	*Developmental English*	*Developmental Math*
Pell-Recipient	43.6%	57.5%	49.6%
First Generation	24.2%	27.3%	27.8%
Full-Time	48.1%	58.7%	66.3%
Age	65.0% ≤24 Years Old 35.0% ≥25 Years Old	79.8% ≤24 Years Old 20.2% ≥25 Years Old	79.2% ≤24 Years Old 20.8% ≥25 Years Old
Gender	43.8% Male 56.2% Female	46.0% Male 54.0% Female	46.1% Male 53.9% Female
Race	53.3% White 21.5% African American 12.0% Hispanic 7.3% Asian 5.8% Other*	34.4% White 34.6% African American 15.2% Hispanic 9.8% Asian 6.0% Other*	44.2% White 19.7% African American 23.2% Hispanic 6.9% Asian 5.9% Other*
Semester GPA (Mean)	2.64	2.22	2.28

**Other includes the following race categories: unknown, American Indian/Alaskan, Hawaiian/Pacific Islander, not specified, and two or more races*

Table 23.

Research Question 1: Treatment Group Characteristics (Mean Scores)

Characteristic	Treatment Groups		
	College-Level	*Developmental English*	*Developmental Math*
Pell-Recipient	53.4%	64.5%	43.7%
First Generation	25.0%	24.9%	24.5%
Full-Time	57.6%	54.1%	62.4%
Age	75.7% ≤24 Years Old 24.5% ≥25 Years Old	86.3% ≤24 Years Old 13.7% ≥25 Years Old	85.9% ≤24 Years Old 14.1% ≥25 Years Old
Gender	47.0% Male 53.0% Female	53.4% Male 46.6% Female	50.6% Male 49.4% Female
Race	57.0% White 25.1% African American 8.7% Hispanic 3.5% Asian 5.7% Other*	29.1% White 48.9% African American 12.2% Hispanic 5.7% Asian 4.0% Other*	38.0% White 20.4% African American 26.5% Hispanic 7.8% Asian 7.3% Other*
Semester GPA (Mean)	1.75	1.63	1.84

**Other includes the following race categories: unknown, American Indian/Alaskan, Hawaiian/Pacific Islander, not specified, and two or more races*

Table 24.

Research Question 2: Treatment Group Characteristics (Mean Scores)

Characteristic	Treatment Groups		
	College-Level	*Developmental English*	*Developmental Math*
Pell-Recipient	53.9%	74.1%	46.9%
First Generation	24.6%	30.3%	23.7%
Full-Time	54.1%	51.1%	59.5%
Age	74.0% ≤24 Years Old 26.0% ≥25 Years Old	78.0% ≤24 Years Old 22.0% ≥25 Years Old	86.3% ≤24 Years Old 13.7% ≥25 Years Old
Gender	52.2% Male 47.8% Female	47.9% Male 52.1% Female	48.9% Male 51.1% Female
Race	55.0% White 26.9% African American 8.2% Hispanic 3.7% Asian 6.4% Other*	33.2% White 51.7% African American 7.1% Hispanic 2.8% Asian 5.3% Other*	42.0% White 19.8% African American 19.8% Hispanic 9.9% Asian 8.4% Other*
Semester GPA (Mean)	1.47	1.13	1.52

**Other includes the following race categories: unknown, American Indian/Alaskan, Hawaiian/Pacific Islander, not specified, and two or more races*

Table 25.

Research Question 3: Treatment Group Characteristics (Mean Scores)

Characteristic	Treatment Groups		
	College-Level	*Developmental English*	*Developmental Math*
Pell-Recipient	53.9%	67.3%	43.1%
First Generation	25.3%	29.1%	20.3%
Full-Time	55.5%	54.9%	61.5%
Age	76.3% ≤24 Years Old 23.7% ≥25 Years Old	84.2% ≤24 Years Old 15.8% ≥25 Years Old	86.9% ≤24 Years Old 13.1% ≥25 Years Old
Gender	48.9% Male 51.1% Female	52.6% Male 47.4% Female	50.4% Male 49.6% Female
Race	53.7% White 27.4% African American 9.1% Hispanic 3.5% Asian 6.3% Other*	30.7% White 49.2% African American 10.8% Hispanic 3.4% Asian 5.9% Other*	38.0% White 21.1% African American 24.5% Hispanic 8.2% Asian 8.3% Other*
Semester GPA (Mean)	1.32	1.02	1.59

**Other includes the following race categories: unknown, American Indian/Alaskan, Hawaiian/Pacific Islander, not specified, and two or more races*

Table 26.

Research Question 4: Treatment Group Characteristics (Mean Scores)

Characteristic	Treatment Groups	
	Developmental English	*Developmental Math*
Pell-Recipient	66.6%	42.2%
First Generation	26.8%	23.2%
Full-Time	53.1%	61.7%
Age	83.0% ≤24 Years Old 17.0% ≥25 Years Old	85.7% ≤24 Years Old 14.3% ≥25 Years Old
Gender	51.0% Male 49.0% Female	50.8% Male 49.2% Female
Race	32.1% White 49.3% African American 9.9% Hispanic 4.3% Asian 4.5% Other*	40.3% White 20.6% African American 25.3% Hispanic 6.7% Asian 7.2% Other*
Semester GPA (Mean)	1.34	1.84

**Other includes the following race categories: unknown, American Indian/Alaskan, Hawaiian/Pacific Islander, not specified, and two or more races*

APPENDIX F

Table 27.

Research Question 1: Results of Chi Square Analysis on Gender and Race between Treatment and Control Groups (p value)

Strata	Developmental English		Developmental Math		College-Level	
	Gender	*Race*	*Gender*	*Race*	*Gender*	*Race*
1	.882	.046	.891	.375	.631	.009
2	.426	.516	.131	.100	.084	.405
3	.080	.289	.110	.076	.187	.033
4	.857	.827	.294	.835	.040	.000
5	.239	.881	.653	.154	.069	.000
6	.229	.464	.542	.671	.680	.000
7	.047	.693	.002	.403	.159	.114
8	.070	.848	.643	.727	.080	.000
9	.298	.001	.355	.016	.000	.000
10	.032	.357	.195	.280	.245	.000
11	.624	.427	.791	.688	.049	.012
12	.846	.715	.448	.246	.494	.003
13	.007	.171	.299	.107	.000	.000
14	.027	.203	.617	.564	.179	.000
15	.829	.939	.515	.272	.032	.000
16	.486	.526	.652	.248	.000	.000

Table 28.

Research Question 2: Results of Chi Square Analysis on Gender and Race between Treatment and Control Groups (p value)

Strata	Developmental English		Developmental Math		College-Level	
	Gender	Race	Gender	Race	Gender	Race
1	.592	.066	.180	.908	.383	.558
2	.226	.606	.072	.118	.002	.112
3	.638	.245	.227	.310	.443	.123
4	.384	.647	.261	.950	.000	.030
5	.965	.026	.767	.066	.045	.000
6	.314	.048	.880	.939	.034	.003
7	.094	.491	N/A	N/A	.065	.745
8	.115	.058	.335	.782	.050	.000
9	.610	.031	.459	.033	.000	.000
10	.758	.085	.127	.824	.001	.001
11	.919	.331	1.000	.906	.000	.174
12	.146	.174	.036	.014	.001	.018
13	.942	.513	.101	.150	.000	.000
14	.228	.242	.533	.584	.000	.000
15	.416	.866	.522	.120	.000	.179
16	.459	.458	.515	.977	.000	.000

Table 29.

Research Question 3: Results of Chi Square Analysis on Gender and Race between Treatment and Control Groups (p value)

Strata	Developmental English		Developmental Math		College-Level	
	Gender	*Race*	*Gender*	*Race*	*Gender*	*Race*
1	.960	.079	.751	.821	.721	.776
2	.426	.680	.268	.005	.167	.540
3	.048	.133	.152	.051	.896	.364
4	.606	.247	.528	.642	.030	.013
5	.443	.059	.727	.697	.102	.000
6	.919	.588	.251	.707	.080	.001
7	.094	.641	.654	.647	.350	.599
8	.347	.635	.360	.323	.232	.083
9	.275	.000	.887	.566	.000	.000
10	.118	.001	.134	.384	.000	.000
11	.725	.768	.750	.641	.000	.006
12	.223	.702	.470	.261	.007	.426
13	.809	.684	.277	.077	.000	.000
14	.058	.305	.261	.395	.160	.000
15	.362	.860	.012	.659	.007	.031
16	.244	.286	.854	.267	.002	.000

Table 30.

Research Question 4: Results of Chi Square Analysis on Gender and Race between Treatment and Control Groups (p value)

Strata	Developmental English		Developmental Math	
	Gender	*Race*	*Gender*	*Race*
1	.722	.081	.617	.513
2	.841	.908	.017	.108
3	.043	.138	.402	.168
4	.767	.343	.134	.848
5	.042	.077	.610	.385
6	.758	.072	.547	.682
7	.014	.943	.034	.211
8	.194	.522	.277	.622
9	.333	.000	.197	.114
10	.013	.004	.080	.815
11	.698	.231	.546	.761
12	.452	.412	.273	.190
13	.089	.083	.139	.082
14	.027	.022	.815	.497
15	.557	.777	.331	.400
16	.993	.491	.758	.310

APPENDIX G

Table 31.

Results: Binary Logistic Regression With and Without Race and Gender for College-Level Groups

Research Question	Variable(s) Entered	B	Wald	Sig.	Exp(B)	95% C.I. for Exp(B)	
						Upper	*Lower*
1	Number of *Academic* Flags Raised	.200	318.405	.000	1.221	1.194	1.248
1	Race; Gender; Number of *Academic* Flags Raised	.199	315.448	.000	1.220	1.193	1.247
2	Number of *Attendance* Flags Raised	-.070	16.657	.000	.933	.902	.964
2	Race; Gender; Number of *Attendance* Flags Raised	-.071	17.252	.000	.932	.901	.963
3	Number of *In Danger of Failing* Flags Raised	.013	.695	.404	1.013	.983	1.045
3	Race; Gender; Number of *In Danger of Failing* Flags Raised	.012	.615	.433	1.012	.982	1.044

**Race was categorized dichotomously with white (dominant) and all other races (non-dominant).*

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Education:

2017 Ph.D. in Community College Leadership
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2006 M.S. in College Student Development and Administration
University of Wisconsin–La Crosse, La Crosse, Wisconsin

2002 B.A. in Communication Studies
University of Wisconsin–La Crosse, La Crosse, Wisconsin

Professional Experience:

Virginia Community College System, Richmond, VA Jan. 14 – Current
Assistant Vice Chancellor of Workforce Policy, Workforce Development Services

- Lead policy development efforts in support of credential attainment, with particular focus on industry certifications and licensures.
- Develop methods and efficiencies in data collection to support the advancement of workforce services and statewide priorities.
- Lead efforts with internal departments and external agencies and organizations to develop or automate programs to analyze student outcome data, such as: student enrollment, retention, program completion, graduation/success rate, employment, and social service dependency.
- Organize and facilitate college and system-level policies and initiatives that will increase business knowledge of and demand for industry certifications and licensures.
- Lead and manage a staff of 15-20 team members.
- Co-lead implementation of the first statewide performance-based funding model for short-term, noncredit training programs.
- Facilitate discussions with internal and external stakeholders to identify industry certifications that matter to business and industry, regionally.
- Provide system office support to 22 community college workforce divisions.

Virginia Community College System, Richmond, VA Apr. 11 – Jan. 14
Director of Educational Policy, Academic Services & Research

- Represent Virginia's community colleges on the State Committee on Transfer and lead efforts to develop system-wide transfer agreements
- Collaborate with Virginia Department of Education and Virginia's community colleges to coordinate state-wide dual enrollment programs, initiatives, and legislation
- Provide leadership for the implementation of a system-wide early alert and retention system
- Support the developmental English redesign initiative and the Chancellor's Developmental Education Institute
- Assist with grant proposals to support and development of programs associated with the strategic plan

Virginia Community College System, Richmond, VA Sept. 09 – Mar. 11
Coordinator of Career & Educational Resources

- Conduct presentations and trainings for targeted internal (e.g., State Board, presidents, vice presidents/provosts) and external (e.g., American Association for Community Colleges, State Council for Higher Education in Virginia, Virginia Department of Education) constituents
- Provide project management, budget and oversight of the advisory board for the Virginia Education Wizard, an online career and course planning tool

Colorado State University, Fort Collins, CO Oct. 07 – July 09
Advisor, School of Biomedical Engineering

- Facilitated communication to promote program development with faculty, college staff, students, and stakeholders
- Developed and managed new degree programs and policy in coordination with a team of faculty and students as well as relevant university and external constituents.
- Conducted research, analyzed data, and prepared a proposal for a new undergraduate program; program launched in Fall 2011
- Created and managed all recruitment, admissions, and advising of students to ensure strong enrollment and academic progress
- Reconciled and generated departmental budget reports
- Created and directed branding initiatives for degree programs and course options

Aims Community College, Greeley, CO July 06 – Oct. 07
Coordinator, Student Success Center

- Conducted comparator analysis in an effort to identify areas for program growth and implemented the programming initiatives; trained staff and students for implementation of programming
- Managed and instituted growth of career services unit by building relationships with community employers and stakeholders
- Provided career counseling and retention/academic advising to a diverse student population; worked with high-risk students to encourage academic and personal development
- Launched and supported programming to support student, employer, and faculty needs
- Supervised and managed career services staff, daily operations, and budget

Dunwoody College of Technology, Minneapolis, MN Apr. 03 – Aug. 04
*Coordinator***,** Custom Training and Continuing Education

- Managed daily operations and ensured delivery of all course outcomes.
- Maintained continual contact with community organizations and internal departments to assess needs and support course delivery