Assessment of Technology Use Data Contribution to Early Alert Efforts at an Access Based Institution

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ABSTRACT

The need for institutions of higher education to be more responsive and results oriented has become more acute with each passing year. Erratic enrollment trends, a shrinking base from which to draw potential students, the external pressures of performance-based funding, increasing amounts of student debt, and increasing costs are all prompting colleges and universities to action. Institutions of higher education are closing their doors as the cost of attending college rises and the number of degrees awarded decreases (National Center for Education Statistics, 2018).

Researching why so many students do not complete college and the ways to effectively intervene to help students be successful has become an important field of study in higher education. The advent of massive amounts of electronic data and the lower costs of storage have given rise to an era of big data analytics. Companies the world over are using big data analysis in an effort to intervene with customers and alter behaviors. Why not begin to do the same in higher education, especially if it can help students be successful?

This research study was performed for the analysis of basic technology engagement data at the individual student level in hopes of applying it to the development of early alert efforts for students who appear to be struggling with their academic work. Wireless logins, campus portal logins and learning management system logins were studied over three semesters at one access-based institution. When added to traditional academic predictors, results suggest that technology engagement data significantly strengthens the accuracy of models intended to flag students who may be at risk.

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DEDICATION

I dedicate this dissertation to my wife and partner, Susanne.
You have given up so much of yourself to allow me to pursue my callings. You are my strongest supporter, my best friend and the best person I know. I am blessed far beyond anything I could have ever dreamt of simply because you are who you are.
I am eternally grateful.

Chapter I

INTRODUCTION

Over the past few decades, higher education has been facing erratic enrollment. Wide swings in economic conditions, rising costs, increased debt and increased questioning of the value a post-secondary degree has to offer have all contributed the volatile environment that institutions find themselves in. Facing increasing political pressure in the United States, many state legislatures have already moved or are in the process of moving toward a performance-based funding model where results are emphasized more than sheer enrollment numbers (Blankenberger & Phillips, 2016).

The issues facing higher education cannot be understated. In one year alone, the number of institutions of higher education operating in the United States dropped from 4,147 to 3,895, with 4-year institutions closing at a faster pace than 2-year institutions. During that time, the price of attending and average student debt increased whereas enrollment and the number of degrees conferred decreased (National Center for Education Statistics, 2018).

At the same time, data clearly show that there is indeed value in obtaining a bachelor's degree. The percentage of 20- to 24-year-olds not in school and unemployed was dramatically less for those with even some college experience (26% for those with no college, 9% for those with some college) (National Center for Education Statistics, 2018). For adults 25 to 34, average annual earnings of those with college degrees was 72% higher (National Center for Education Statistics, 2018). These statistics should be convincing enough, so why is enrollment so volatile and why are political and funding pressures mounting? The time and cost necessary to attain a degree have increased whereas the return on investment (based on the size of that investment) takes years to realize which, for many, is too slow.

In the face of these mounting pressures, institutions of higher education find themselves answering questions about their value and purpose on one side while attempting to understand retaining and graduating students on the other. This situation has given rise to many studies in search of answers that can strengthen the promise of higher education and help more students succeed.

Why students succeed at the college level has been a major focus of much of this research. Students attending college for the first time drop out at higher rates during or after the first year than at any other time. "For an average institution, freshman to sophomore year attrition is about 25 percent; sophomore to junior year attrition is about 12 percent; junior to senior year attrition is about 8 percent; and about 4 percent of seniors might leave school" (Bean, [ca. 2001]). This general pattern is reinforced by the National Student Clearinghouse Research Center (NSCRC) which tracks students throughout college and graduate school and publishes yearly reports on persistence and completion rates.

Reports tracking first time, full time freshman over six years reveal how many students persist at their starting institution from the first year through the sixth year. Some students graduate during those 6 years, whereas others transfer to different institutions. Over the 6 years, however, students also drop out of college completely. Of those who started college at a given institution in the fall semester of 2013, approximately 23% did not return to the same institution in 2014. By 2015, and additional 16% did not return. By 2016, and additional 3.8% had left their starting institution (National Student Clearinghouse Research Center, 2020).

The numbers are similar for each year. Using the same report from the NSCRC (2020) and averaging the tracks of first-time full-time freshman from the starting years of 2011, 2012 and 2013, approximately 25% of students left the institution after the first year. An average of 15% of those who came back left the institution the following year, and 4% for the year after that (National Student Clearinghouse Research Center, 2018, 2019, 2020).

For an institution that starts with 1,000 students, these percentages would indicate a loss of 250 students in the first year, 112 students in the second year, and 25 students in the third year. On average, then, more students leave after the first year of college than any other time. The second year is somewhat less volatile with diminishing attrition in subsequent years.

Although some consider this phenomenon a metaphorical natural selection eliminating those who are poorly prepared or even capable of college level academics (Duguet, Le Mener & Morlaix, 2016), many studies and intervention methods have been tested to address this specific issue. Admission selection and criteria, orientation, quality of faculty in first year courses, student life, campus activities, access to technology, on campus living, commuting students, tutoring, supplemental instruction, advising, mid-term grades, remedial programs, first year curriculum and countless other angles have all been researched to see how colleges and universities might begin to improve at keeping more students in college and progressing.

Several studies have begun to cast a wider net to look at student behavior both inside and outside the classroom. Measuring what researchers have termed "*student engagement*" has become the focus of many recent studies. Despite not having a fully agreed upon definition, student engagement is seen as a major piece to the ongoing puzzle of student success (Fredricks, 2011). Understanding how successful students behave in a broader sense may provide stimuli and useful data to future intervention program development.

The issue with the research in this all-encompassing field is that much of it is retrospective, introspective, and subjective. Previous studies have largely relied on faculty, staff, and administrators to observe and note student engagement or surveys of the students asking them to rate their own levels of engagement or describe their own behaviors. Combining past indicators of success with current engagement observational data also appears to be an area that needs continued study.

In the past, this approach would probably be the only pragmatic course of action. As an example, consider electricity services to homes. To fully understand the use of electricity and ultimately charge customers the correct amounts, the utility company had to rely on observational data collected by individuals who traveled throughout the service area and physically read each and every meter at every home. The process was slow and the observations were spaced out on a monthly basis. These data were incredibly valuable to the utility provider and allowed them to model yearly cycles of peak monthly demand as well as comparative data between household behavior (use of electricity).

However, as technology progressed, smart meters have been introduced to most communities and the utility companies can now see what is happening in real time. At any second of any day, the utility company can know the exact consumption rate of any household it chooses. In fact, cell phone usage, location data, dashboard cameras, body cameras, personal digital assistants, smart speaker devices, which are always recording (Martinez, 2017), global position, autonomous lane steering/braking vehicles, websites, surveillance cameras, refrigerators, thermostats, and even freestyle Coca-Cola machines (Wong, 2017) are all collecting behavioral data all the time.

These massive amounts of behavioral data are stored and analyzed using ever-increasingly intelligent algorithms, which are extremely valuable for their observational and predictive nature. If we can predict future behavior or outcomes based on these data and algorithms, then the right intervention at the proper moment can alter behavior and perhaps change not just an individual's future, but many more.

Big data is available and within reach of most colleges and universities. Some of them even offer degrees in big data research. At some levels, higher education is already taking advantage of this. The University System of Georgia collects massive amounts of student data from all of their institutions throughout the state into a large data warehouse, which are then analyzed and used to promote changes both at the state and institutional levels to improve the student experience in many ways.

One of the most recent examples of using big data to affect changes in the student experience has resulted in the University System of Georgia investing resources into a concentrated effort called the "Momentum Year". "Momentum Year is a suite of strategies designed to help University System of Georgia students in their crucial first year of college. We work with student to guide them on a path to achieve their educational goals, including successful degree completion and on-time graduation" (University System of Georgia, 2019, p. 1).

Data collected from system institutions generated several insights that affect student success during their first year of college. Institutions that started students in remedial courses and delayed the first-year core English and mathematics courses have been shown to actually lower the student's ability to persist and progress. As a result, the Momentum Year initiative requires that the first year of courses includes these core classes and instead emphasizes support courses for those students who need them (University System of Georgia, 2019). Analysis of the data also indicated that students who attempt at least 30 or more credits total in their first two semesters increase their 6-year graduation chances by 12 percentage points and actually earn an average of 15 more credits in their first year than their counterparts (2019).

Policy changes that help students build momentum during their first year in college are a direct result of big data analysis. The data used in these analyses were collected from state colleges and universities over many years and these conclusions came from looking at what students accomplished given their course load and specific courses during the first two semesters in college. Looking back at what happened, analyzing and affecting change using those results is an important tool for research and program evaluation.

Although it may not be considered big data, there seems to be a gap in research concerning institutional level data and how it might be used to analyze student behavior at a faster, automated pace and, perhaps, predict outcomes. Unless one turns off location services, cell phone companies know where their subscribers are at all times and even ask them to rate their visit or offer them suggestions without the user prompting the phone. These companies use this nearly real time data combined with algorithms that get smarter over time to prompt interventions. Why not use these same techniques at institutions of higher education?

Problem Statement

Most college campuses today offer a bevy of technology services that require students to login, such as wireless networking, portals and even mobile applications. These tools can provide a wealth of nearly real time data that might be used to better effect if the information to be harvested can be found to have any significance. On most college campuses, the data in question may or may not already be available depending on collection techniques, storage capacity and perceptions on the value of such data. Alternatively, this type of data might be used in disjointed ways by different organizations within the institution. Wireless access, for instance, might be something that typically only information technology departments find valuable, whereas mobile application use would be more valuable to student life.

When it comes to intervention strategies, some research and effort has been made towards early alert systems. These systems rely on technology to facilitate a process wherein faculty initiate either positive or negative flags on student performance. The early alert system then notifies students, advisors, administrators, tutors and any number of departments that can all choose to intervene (Faulconer, Geissler, Majewski & Trifilo, 2013). These systems, in effect, are an automated communication tool that forces a certain procedural change at the front end where faculty need to engage in perhaps a different way than they ever have.

Although incredibly valuable, such systems still rely on human observation and initiation. To be clear, college faculty are certainly the most qualified to gauge academic standing in a course while there is still time to intervene in the situation. However, there are many student situations that faculty may not be aware of that could ultimately affect academic performance. Being able to give faculty and others a signal that all may not be well with any given student before it becomes obvious is necessary if institutions are looking to help students in need.

Questions

If retaining students is an area of concern for institutions of higher education, then finding effective ways to assist students in need must continue to be researched. Before colleges can help those students, however, institutions must be able to identify them. Effective research can continue around the topic student engagement and what indicators might predict success by looking at results, then formulating and adjusting strategies and assessing new results.

While this cycle continues, how can institutions compress the timeline and adjust much more quickly so that current students can reap the benefits of strategies intended to help retain them and progress? Is it possible for institutions to take advantage of the massive amounts of data they have access to in new ways and in real time so that interventions have the chance of being timelier and more effective?

Institutions have a wide array of technology offerings both inside and outside the classroom. At a collegiate level, access-based institution with relatively low selectivity, can technology systems activity by students be used as a predictor of success as defined by term grade point average (GPA)? These questions are the focus of this research.

Organization

This chapter of the dissertation provides an introduction and overview to the problem and purpose for the research. The next chapter provides a look at related literature in the field including theoretical frameworks and prior research. Chapter 3 provides an overview of the methodology used to perform the data collection and analysis. Chapter 4 presents the results of the analyses and Chapter 5 provides for discussion and recommendations. Appendix A lists the results of the descriptive analysis, Appendix B list the result of the regression analysis, and Appendix C provides the set of Institutional Review Board (IRB) authorizations for this research.

Chapter II

LITERATURE REVIEW

Theoretical Basis

Success in higher education depends on a wide variety of factors. Some of these factors have been researched, some are popular research topics and others have not been studied at all. Many factors that contribute to success in college overlap and are difficult to measure (Duguet et al., 2016). As students transition from high school into college, many aspects of their daily lives change and some students find it difficult to adjust. This is especially true for students who are the first in their family to attend college.

Some of the numerous factors that contribute to student success at the collegiate level include family support; community support; college preparedness; college culture; classroom experience; interactions with faculty, staff, and other students; finances; perceptions; student motivations; and study skills (Kinzie & Kuh, 2017). With such a wide array of influences, institutions that desire to study the reasons for students failing and/or dropping out of college have many places to look.

As this type of research has become more popular, multiple frameworks have been built under the umbrella term *student engagement*. In theory, students who are fully engaged at the collegiate level will experience a higher rate of success than they otherwise might. Students who attend class, interact with faculty, participate in discussions, learn and receive support from their peers, and spend time studying the subject outside of the classroom might be considered engaged and therefore have a higher chance of producing a more desirable outcome.

The Student

The study of student engagement has incorporated many aspects of student personalities that can be difficult to measure and somewhat subjective to interpret. Traditionally, the notion that higher education is not for everyone has, in some ways, allowed institutions to take a colder stance towards first year students who wash out of the program (Duguet et al., 2016). This idea, however, has become increasingly difficult to fall back on in an era when the value of holding an advanced degree is clear.

Students of all capabilities and background circumstances are encouraged to seek a higher education which is, at least in some small part, why there are a wide variety of institutional types and classifications with comparably different missions. Ivy league universities, for example, are designed to engage a particular type of student with certain levels of academic history and demonstrated capability. On the other hand, colleges whose mission includes access are designed to serve students who would not otherwise be afforded the opportunity to earn a degree.

Part of the challenge, then, with student engagement is the academic preparedness, inclinations, and capabilities of the students themselves. Some students are naturally academic, whereas others have to work very hard. The seminal American inventor Thomas Edison is quoted in many different forms as stating that “I never did anything worth doing by accident, nor did any of my inventions come indirectly through accident, except the phonograph. No, when I have fully decided that a result is worth getting, I go about it, and make trial after trial, until it comes” (Dreiser & Hakutani, 1985,

p. 118). What Edison was essentially saying is that hard work, not genius or accident, is what ultimately produces results.

The same can be said of some students when it comes to academic endeavors. The ability to persevere in effort, sometimes called "grit," has been categorized and measured in some research (Muenks, Wigfield, Yang, & O'Neal, 2017). Although the results indicated that a measure of grit could be used to predict grades to a certain degree, it has not proven as useful as measures of other personality traits such as self-regulation and self-control.

Others have found that study and learning skills possessed by students can be measured and appear to play a significant role in the prediction of student success when compared with these other personality traits including sheer will and self-regulation (Enikö & Szamosközi, 2017). When taken as a whole, these student-focused traits can be thought of as a student's disposition to learning. This intrinsic disposition to learning is certainly vital to engagement (Goldspink & Foster, 2013), but reliably measuring it can be very challenging. To be able to affect it, to alter a given student's disposition, self-control, and propensity to persevere, is another challenge all together.

The Classroom Experience

Although colleges and universities may have little success in directly altering intrinsic student personality traits, they can influence students and yield greater impacts in the classroom experience. Direct faculty and student interaction and the student experience in the classroom can foster engagement or discourage students from investing time and attention. The classroom experience will influence student engagement probably more than any other connection to students.

The ability of an institution to link academic material and practices to a student's existing knowledge base and their areas of interest is a prerequisite for engagement (Goldspink & Foster, 2013). The material must be made tangible and encouraging. Students who arrive at college and find no connection between their academic coursework and the foundation they have coming in will likely feel lost. Without a few guideposts to point them in the right direction, those feelings may soon turn into despair with each passing exercise and ultimately to resignation.

Hope and help, of course, can come from classmates, faculty and other services such as supplemental instruction and tutoring. However, from the outset, most students are not aware of these support services and have not formed the necessary relationships with their peers in order to take full advantage of them. This may be why there is a wealth of research and support for learning communities.

Learning communities are purposely designed by faculty to ensure that first year students, as much as possible, are taking a prescribed set of courses with the same group of students in every classroom setting. These cohorts, then, quickly become familiar territory and students become less anxious and more open to discussion. Learning communities seem to produce even stronger results when the faculty teaching each of the cohort's courses coordinate with each other and create connections between assignments in different courses. In this way, courses help to strengthen learning in other courses and students can begin to understand different perspectives on the same material. If a student has trouble from one perspective, they might see enough guideposts in a different course to help them understand the subject matter.

Students who participate in learning communities in which they have courses and study with the same group of students engage to a higher degree because they are more comfortable. These students tend to persist on average 5 and 15% more than students who do not participate in learning communities (Engstrom & Tinto, 2008). These students describe learning communities as providing safer, supported environments that produce a sense of belonging in college and deeper learning. These types of cohorts are especially important at community colleges, where students are much less likely to be involved with student life and with other students (Tinto, 1997).

This is not to say that students need a completely comfortable situation in order to engage. Being familiar with their peers and experiencing a coordinated curriculum can help to create an environment conducive to student engagement, but students must also feel challenged. Classroom communication and strong interactions with faculty are certainly important. At the same time, research has shown that students who feel the appropriate amount of stress and time pressure also perform better academically (Aydin, 2017). Too much comfort and not enough intellectual stimulation can result in non-challenging coursework, boredom, and disengagement.

It is clear, then, that the classroom environment, how students are not only challenged but also supported, is critical to encourage student engagement. Strong classroom interactions, excellent faculty who communicate well with students and coordinate with other faculty, familiarity with peers, and a safe environment for participation are all crucially important. Institutions have direct control over creating such environments which foster engaged learning and can ultimately help more students succeed academically.

The College Environment

Academic involvement alone does not constitute student engagement. According to Tinto (1997), a foundational scholar in the field of student engagement, student involvement in the life of the college, their investment of time and energy in their whole education, is related to their success in college and persistence. Therefore, an engaged student is one who participates in the entire college experience, including activities and organizations that are traditionally under the purview of student life.

Participating in clubs, organizations, campus-related activities, athletic events, other extra-curricular events, and even residence hall living are indicative of students who are engaged in the life of the college. It is through some of these nonacademically focused activities that students form strong bonds with their contemporaries and build the support structures that are sometimes needed when academic and life events present challenges. Often, the only way to overcome these challenges is with the assistance of others through direct or indirect knowledge, or even simple presence and support.

Students engaged in the life of college outside of the classroom are also more likely to interact in nonacademic ways with faculty, staff and administration. Outside of other students, the employees of the institution embody the ethos of the institution. Is the college a supportive, energetic and caring environment, or is it a cold, uncaring, and unforgiving atmosphere? Are the employees selfish or selfless? In other words, are the employees of the institution truly student focused and concerned about their success? The culture of an institution can make a tremendous difference in whether or not a student truly affiliates with the college.

Social capital, or the ability of students to connect, communicate and work with peers and mentors has been found to be very important to engaged learning (Deepak, Wisner, & Benton, 2016). Other studies have demonstrated positive correlations between a student's ability to adjust to college life (both academically and otherwise), student engagement and academic performance (Goudih, Abdallah, & Benraghda, 2018).

The college environment and campus climate matter when predicting academic outcomes (Soria, Fransen, & Nackerud, 2017). This investment of the whole student, the way students spend their time in both academic and nonacademic endeavors, has become an important marker in the research of student engagement. The ethos of a college, including what happens in the classroom, at athletic events, drama and musical performances, the library or learning commons, and other student activities can make an important contribution to engagement and academic success.

Student Engagement Frameworks

These three key areas of focus for student engagement – intrinsic student personality traits, the classroom experience, and the college environment are all vitally important to understanding how students succeed or not in college. Many studies of student engagement do not encompass all of these areas depending on the interests of the researchers and the intended outcomes of the exercise. Ultimately, the goal of research in the area of student engagement is to understand what fosters student investment and what institutions can alter to help more students succeed.

When the term *student engagement* is employed, it can be difficult to know exactly which facet of engagement is being discussed. To most faculty, the term *student engagement* might mean something completely different than it does to student life practitioners, administrators, or researchers with varied backgrounds. One study might look solely at student behavioral indicators, whereas other research will use the term to study emotions.

In an attempt to help describe the field of study, organize the immense range of research and give meaning to the term *student engagement*, several frameworks have been put forward by researchers. Many of these frameworks overlap each other and even the internal dimensions within a single framework are not distinct.

School Engagement Framework

Fredricks, Blumenfeld and Paris (2004) presented a framework for student engagement that combined previous research into three major umbrellas of engagement. Behavioral engagement, emotional engagement, and cognitive engagement are presented as overlapping dimensions of their framework.

Behavioral engagement encompasses several levels of behavior which Fredricks et al. (2004) detail as good conduct, involvement in the classroom and involvement in extra-curricular activities. This type of research concentrates on whether or not students meet behavioral expectations of the institution (attending class, being nondisruptive), take steps to engage in the classroom with their learning (asking questions, participating in discussions) and are involved with the life of the college outside of the classroom (attending concerts, being part of clubs).

Emotional engagement encompasses how students feel about the school and react to faculty, staff, administrators and any given situation (Fredricks, Blumenfeld, & Paris, 2004). The concept of affiliation is important in emotional engagement. Students who identify with the school and experience positive feelings have higher emotional engagement with the institution than those who do not.

Cognitive engagement encompasses student strategies for approaching their academic pursuits. How students go about their work, how much effort they put into understanding complex concepts, and whether or not they are motivated to learn are all included in this cognitive umbrella (Fredricks et al., 2004).

Fredricks (2011) later extends this framework to include out-of-school contexts and drew an important distinction between structured, supervised out-of-school activities versus unstructured and unsupervised. Students who participate more in structured activities tend to do better academically.

Engagement in Science

Sinatra, Heddy and Lombardi (2015) presented a framework for student engagement that looked at research being on a continuum. They began with a review of Fredricks' multidimensional school engagement model and posited that the model is insufficient to explain or measure student engagement in science. Because science, as a field, has unique engagement requirements, any model that would be applied needs to overcome or explain epistemic cognition, scientific practices, misconceptions, emotional topics, attitudes toward science and gender, minority, and identity issues (Sinatra et al., 2015).

To overcome these limitations of the multidimensional school engagement model in science, Sinatra et al. (2015) suggested that researchers should be aware of and state both the dimension of engagement being studied along with the grain size of analysis. Grain size, or unit of measurement, can be described on a continuum as well.

Researchers can study engagement that is person-oriented, person-in-context, or context-oriented in nature.

Person-oriented research is focused on student motivations, personality traits, emotional reactions and cognitive effort (Sinatra et al., 2015). The important distinction here is that the research unit of measurement (grain size) is the individual student. At the other end of the continuum, context-oriented research is focused on the environment the student is in and includes concepts such as culture, community, support structures and so on. In the middle of the continuum, then, is the study of person-in-context which seeks to understand how students interact with different aspects of the environment they are in.

Considering the three areas of intrinsic student personality traits, the classroom experience and the college environment, there is a relationship to the framework presented here. As in other frameworks, Sinatra et al. (2015) are careful to point out that research dimension and grain size are not exclusive. In other words, researching the individual student may uncover data concerning the environment and how they interact with it.

Online Engagement Framework

Another framework for student engagement also builds upon the initial three aspects of behavioral, emotional and cognitive. Redmond, Abawi, Brown, Henderson, & Hefferna (2018) suggested that to study the engagement of students taking courses online, additional types of engagement need to be added to form a complete framework. In addition to the behavioral, emotional and cognitive types of engagement, Redmond et al. (2018) added in collaborative and social engagement.

By adding collaborative and social engagement types to their model, Redmond et al. (2018) indicated that interaction with others is an extremely important aspect of engaged learning in the online format. They noted that behavioral engagement includes indicators of supporting and encouraging peers, so there is considerable overlap in this multidimensional model as well, which the authors point out.

Social engagement is concerned with some of the same concepts previously mentioned such as building community, affiliation, and relationships (Redmond et al., 2018). Collaborative engagement encompasses how students work together, learn from each other, relate to faculty, and build professional networks. Redmond et al. (2018) suggested that faculty teaching online should consider all five dimensions of this framework in an effort to foster engagement.

Measuring Student Engagement

The breadth of research and definitions related to student engagement has given rise to many frameworks. These frameworks are an attempt to bring some structure to the concept of student engagement so that the same terms used in different studies are not confused as having the same exact definitions. These multidimensional frameworks also are indicative of the breadth and difficulty of measuring student engagement.

Various research tools such as the National Survey of Student Engagement (2018) categorize engagement indicators into four general themes: academic challenge, learning with peers, experiences with faculty, and campus environment. The same themes run through each of the frameworks presented. Other measurement tools used in research may concentrate on one specific dimension, but all are encompassed by these frameworks. The vast array of research and tools serve to represent the difficulty of wrestling with conflicting outcomes and the uniqueness of institutional situations when it comes to measuring engagement.

Attempts to measure student engagement are largely self-reported, such as the NSSE, or relying on human observation in one form or another. However, even faculty observation can be misleading. Students can be very good at pretending to engage in a classroom setting (Fuller, Karunaratne, Naidu, Exintaris, Short, et al., 2018). Even specially trained observers have been fooled by students who later self-reported that they were not really engaged.

Example studies of predictive analytics also demonstrate the difficulty in generalizing local results. Starting with different definitions alters the results of the analysis. Without a set of common definitions for data points, comparison of results across institutions and a theoretically common approach to intervention is useless. Many attempts have been made to synthesize data from numerous institutions in an effort to create some common understanding. The Predictive Analytics Reporting Framework (PAR) initiative is one such project. Consisting of approximately 20 universities and colleges, the goal was to begin building a common understanding of data points, intervention methods and to provide benchmarking for member institutions (Wagner & Longanecker, 2016).

The issues with reporting of data to use for predictive analysis are numerous and such initiatives are indicative of these intricacies and the need to have a clear understanding from the beginning.

In addition to plethora of definitions, measuring the broad spectrum of engagement is a difficult and complex proposition. Studying specific aspects of engagement appears to be the most navigable course of action (D'Mello, Dieterle, & Duckworth, 2017). The most widely used measures of engagement are self-report questionnaires (D'Mello et al., 2017).

Of course, several issues can affect the quality of the data being analyzed. One student or teacher may use completely different standards when asked about engagement (D'Mello et al., 2017). Consider the question of whether or not the course and the faculty were challenging the student to grow. One student may use the standard of cognitive difficulty whereas another may use the standard of quantity of work to answer the same question.

In measuring teacher strategies against outcomes, one study found that teachers who used evidenced-based instruction had a more positive effect on students than teachers who concentrated on behavior management techniques (Lekwa, Reddy, Dudek, & Hua, 2018). Faculty, then, have an enormous impact on student learning and their choice of technique can alter the intended outcome. Likewise, their tracking, and reporting of student progress as well as intervention strategies can be individualized and differ from faculty to faculty.

In traditional early alert systems, the primary method of initial alert was through the faculty. However, some faculty may not consider a student in danger whereas another definitively would. Therefore, the viewpoints of individual faculty may alter the reliability of data reported into any predictive analysis.

It is perhaps not surprising then, that student engagement has been found to positively correlate with academic achievement. However, some studies have not demonstrated any correlation, which may be due to various recording methods which can modulate results (Lei, Cui, & Zhou, 2018). In some cases, methods that rely on self-reporting are less reliable than observational methods. It may also be that a study may concentrate on one dimension of engagement when other dimensions in the environment are more useful. For example, one study found that the rates of persistence and success was higher for students who had better support systems and smaller classroom sizes, but that living on campus was not a significant predictor even though that may be the case for some institutions (Millea, Wills, Elder, & Molina, 2018).

Even data-driven reporting using the learning analytics engines of course management systems has been questioned in terms of effective predictive capabilities. Strang (2016) analyzed predictive characteristics from Moodle, a course management system, which demonstrated no significant positive relationship between amount of access and final grade. In fact, there may have been a negative relationship. Strang proposed several reasons why these findings might have been affected including a small sample size, a specific curriculum, higher than average international students in the course being studied, and even that the students who spent less time in the system may have downloaded their assignments and worked offline.

Even when the human observational component is removed from the equation, there are still a myriad of variables that can affect reporting of interactions and change the resulting assessment of student engagement.

Finally, it is important to note that part of the difficulty in researching student engagement is that students are not on one side of engagement or the other. Engagement is not a binary proposition (Pittaway, 2016). A student is not always engaged or disengaged. Some students may be more engaged in some courses while less in others depending on the time of day, the day of the week, or even the time of year. Just as the frameworks are multidimensional continuums, students engage on a continuum as well.

Prior Research

Technology

When it comes to incorporating technology into these student engagement frameworks, research on technology acceptance has indicated that technology must be seen as both comfortable and useful. Specifically studying the willingness to engage with a Moodle based learning management system, Yeou (2016) found that acceptance and engagement requirements were similar in both fully online courses and blended instruction environments. Institutions can foster engagement in learning management systems by first helping students feel comfortable with the technology and then making sure that the content and requirements address the perceived usefulness of the system itself (Yeou, 2016).

However, as Tinto (1997) indicated concerning the classroom experience, the quality of the interaction with faculty inside of the technology tool has been found to be the most likely factor to affect student intention to engage with the technology as opposed to the technology's perceived capabilities (Sun, Lee, Lee, & Law, 2016). Technology itself does not produce student engagement. It is the quality of the interactions with faculty, interest in the subject, quality of course activities, and discussions with peers that have the greatest impact on engagement.

Although technology tools alone are not capable of increasing engagement, they do have the ability to become barriers or, at the very least, discourage engagement if the tools employed are not reliable, easy to use, and seamless. At the same time, technology interaction can indicate engagement. Some studies have indicated a positive correlation between technology use and academic performance (Kuh & Vesper, 1999).

Predictive Data

Specific research using technology-related data to predict student outcomes within these frameworks is scarce. However, as technology and big data become more prevalent and practical, what research there is demonstrates promise.

Learning management systems have provided a wealth of data to mine, and although some research has not found positive correlations between online activity and academic success, many other projects have found that lack of activity may be a strong indicator of students at risk. Abdous, He, and Yen (2012) studied data mining of a public research university's learning management system and found no correlation between online activity and final grades. However, the system being mined for data was not a typical learning management system such as Moodle, Blackboard, or Desire2Learn. These systems are largely asynchronous whereas the data collected by Abdous et al. was of a synchronous live video streaming system.

Learning management system data, however, can be used to predict academic outcomes in some cases. Macfadyen and Dawson (2010) researched learning management system data to see if an early warning system for students at risk could be developed. They looked at the number of discussion messages posted, the number of email messages sent, and the number of assignments completed. Using these indicators of activity, the model that Macfadyen and Dawson (2010) developed correctly identified 81% of the students who failed the course.

Akhtar, Warburton and Xu (2017) developed custom software to collect passive data, without user interaction, in a live, face-to-face environment. The research indicated positive correlations between student achievement and attendance, social stability – how often students worked with the same group, and time spent on any given task during the class (Akhtar et al., 2017). These results indicated that there are factors that can be measured using technology in the learning environment and that such data can be used to build early warning systems to identify students who are at risk.

These effects seem to be even stronger when combined with traditional academic performance predictors. Aguiar, Ambrose, Chawla, Goodrich, and Brockman (2014) used electronic portfolio system usage data to develop a model for predicting engineering student persistence. When using only traditional academic performance data, such as GPA, test scores and even demographics, the researchers were only able to identify 11 of the 48 students who dropped out after the first semester. However, by adding electronic portfolio interactions, specifically logins and hits, they were able to correctly identify 42 of the 48 students who dropped out. In this study, they found even electronic portfolio data alone to be a better predictor of persistence than traditional academic indicators on their own.

It may be that technology use is not a good indicator of engagement – but that lack of technology use is an indicator of disengagement. In researching student interactions in asynchronous online courses, Shelton, Hung, and Lowenthal (2017) found that it is not the total number of interactions in an online course that indicate students who might be at risk. Rather, it is the inconsistency of interactions over time that indicates students who are at risk in a particular course.

Policy Implications

Although researching the effectiveness of various intervention models is not the focus of this project, it is important to be aware of policy implications. If students at risk can be identified sooner, then institutions should be able to alter intervention strategies appropriately.

The purpose of seeking out predictive indicators is to provide extra support and intervene with students before it is too late for those students to be successful in any given semester. Finding easy to measure and timely indicators that can bolster the accuracy of traditional data will be critical to increase the speed at which intervention can be effective.

Intervention is not cheap. It takes personnel time and extended effort from many across an institution to be successful. These costs can quickly add up, especially at access institutions where students may be less prepared for college life and academic work. Institutions need to be aware of the costs and strategic in their investments in order to both have the highest measurable impact in a controlled environment.

Intervention strategies can be categorized into sorting, supporting, connecting and transformation strategies (Perez, 1998). Sorting students into groups so that different and appropriate intervention strategies can be introduced is an important step. Such strategies include assessment scores, full-time versus part-time students, high school grade point average, age and even ethnicity.

Supporting students in nonacademic ways is also an important strategy in that helping to address some of life's daily issues can remove distractions and help students focus on academic work (Perez, 1998). Connection strategies are used to enhance communication between students at risk and their faculty, staff and their peers, which is where learning communities have been seen to be incredibly powerful. Finally, transforming strategies involve remedial and student success courses, advising, counseling, helping faculty to learn new strategies and addressing institutional culture (Perez, 1998).

Early alert systems facilitate communication and bring to bear the village approach to helping students who are at risk. Once students are flagged, faculty, administrators, advisor, tutors, and other staff are alerted and the appropriate contact can reach out and follow up with the student. Where these systems have been introduced, faculty and students often report satisfaction with the system because it fosters communication between the student and the rest of the support structures in the academic community (Faulconer et al., 2013).

However, it is important to note that messages generated via early-alert systems need to be personalized. The initial contact with the student should be as personal as possible, offering students specific and concrete steps in order to improve (Cai, Lewis, & Higdon, 2015).

Wright, McKay, Hershock, Miller and Tritz (2014) used learning analytics to bolster student success in gateway science courses. This custom-developed intervention and coaching system made use of big data learning analytics to deliver personalized learning support to students who wished to use the system. The study produced better than expected results finding that students who used the system more often improved their grades in the courses by 0.17 over what analytics predicted their incoming GPA would actually be (Wright et al., 2014).

Another style of intervention, goal engagement theory, in which students are expected to internalize multiple behavioral and self-regulatory strategies in an effort to help focus through significant life changes, such as the transition from high school into college, appears to be beneficial to students who have been identified as having multiple risk factors. Such goal engagement treatments have helped students increase their grades and their odds of persisting significantly (Hamm, Perry, Chipperfield, Parker, & Heckhausen, 2018).

Writing has also been a focus of intervention strategies. Writing has been seen as an important component of increasing student engagement, and faculty, no matter the subject, can promote engagement through thoughtfully planned writing and collaborative assignments (Huskin, 2016). These assignments do not need to be long or laborious as even short, collaborative, in-class writing promotes thinking and engagement.

No matter the intervention strategies employed, they need to be "wise" in that they promote positive communication. Wise communication aligns the feedback with specific desired outcomes, communicates high expectations, and affirms the student's ability to meet those expectations. These techniques also encourage two-way communication between the student and those who are trying to help (Thayer, Cook, Fiat, Bartlett-Chase, Kember, et al., 2018).

This is, at least in part, why interventions are difficult and possibly expensive. Effective intervention starts with good communication but must include adaptability in the institution and participation from all stakeholders, not just the faculty. Traditional areas of intervention such as orientation, math and English tutoring, academic counseling, career advising, student activities, and mentoring must all work together and adapt interventions to the specific students who need help (Gonzalez, 2000). In an access school, such as the one in this study, there are a myriad of student types from traditional freshman to senior adults, not to mention the diversity of cultures and preparatory experiences. Each of these students are individual learners who respond differently to interventions. The same intervention that motivates one student may produce no effect in another.

Hypotheses

The purpose of this research, then, was to study the data collected at one access institution to see if lack of technology use can be used in conjunction with traditional academic success predictors to flag students who might be at risk during any given semester. Regarding this research, the following hypotheses on the effects of using big data techniques in early alert processing were tested:

Hypothesis 1: In a comparison of students' technology usage behavior, there is a positive relationship between the volume of basic technology engagement and the percentage of credits earned over attempted.

Null Hypothesis 1: In a comparison of students' technology usage behavior, there is no relationship between the volume of basic technology engagement and the percentage of credits earned over attempted.

Hypothesis 2: When combined with traditional academic performance predictors, the volume of basic technology engagement by students strengthens the predictive accuracy of performance.

Null Hypothesis 2: When combined with traditional academic performance predictors, the volume of basic technology engagement by students does not strengthen the predictive accuracy of performance.

Originally, there was a third set of hypotheses proposed that were removed for two reasons. First, this third hypothesis was intended to test the opposite side of the first hypothesis. That is, is there are positive relationship between the lack of basic technology engagement and lower academic performance? Instead of being a distinct hypothesis, this would have been an alternate hypothesis to the first one.

The second reason for removing this third hypothesis has to do with the feasibility of testing it using the research data and methods available. A method for testing this third hypothesis apart from the first one became increasingly elusive and impractical as the methodology was more fully developed. For these reasons, the third hypothesis was removed from this effort.

Chapter III

METHODOLOGY

The goal of this research was to evaluate the validity of using big data gathering and analytical techniques to more quickly and accurately identify students who are at risk during any given semester. This research was designed to be quantitative and used existing academic and system log records.

No students or faculty at the college being studied were identifiable through any reporting of the results, and significant steps were taken to protect the data and any personally identifiable information. Names, addresses, phone numbers, and college assigned identification numbers were never be part of the dataset. A random identification code was assigned to each student with a separate and secure database used as a conversion from the random identification number to the student identification number assigned by the institution. This conversion data were secured physically separate from the extracted data, which was only necessary because the data came from different sources and needed to be tied together. All of the data were extracted at once, and the conversion table was destroyed. Only the primary researcher had access to the data at any time.

Definitions

For clarity and the purposes of this study, two related terms had to be defined from the start. Success in college can be measured in numerous ways. However, the chosen method for this study necessarily had to relate to the period of time that was being researched. Likewise, the term *at-risk* can mean many things and changes based on perspective and objectives. It was necessary to operationalize these two terms in order to attempt to address the primary research questions.

Success

For the purposes of this study, success needed to be something that is term-based due to the focus of the research. In order to elucidate techniques to indicate struggling students within a typical college semester, the measure of success needed to be based on that semester. Other measures of success, such as graduation rate, retention or progression are certainly useful, but are longitudinal by definition.

Term GPA is one logical choice. However, this measure had the potential to introduce several issues. First, the grades themselves can be affected by course load, program of study, or even typical differences in courses between Spring and Fall semesters. Although core curriculum courses are offered nearly every semester, others are usually offered on a rotating schedule every other semester and even every other year in some cases. Even with an extensive number of students, it would not be possible to study every possible combination of courses a student could take during one semester.

In addition to the possible combinations, students take different majors and are interested in different career paths. One student may study journalism whereas the next wants to study medicine. Each of these students would take vastly different courses, especially after their first year. That is not to say that one major is more difficult than another, just that student experiences, circumstances, and work load will vary, which has the potential to disrupt attempts to identify struggling students with any one method.

A further complication with term *grade point average* is that students start at different levels. For some students, anything less than a 3.75 would not be considered success. At the same time, another student who has an incoming cumulative grade point average of 1.8 and is on academic probation might end up with a 2.2. Faculty and advisors would consider that student successful as they made progress in improving their grades.

One way to work around the some of the issues surrounding term GPA might be to calculate an expected term GPA for each student based on their cumulative college GPA so far or their final high school GPA if the student is an incoming freshman. In this way, the measure of success is based on whether or not a student performed better than expected and by how much, worse than expected and by how much, or as expected. Although this may solve some of the issues with term *GPA*, it does not eliminate them completely.

There was, however, another way to measure term-based success that carried fewer issues. Students who enroll in courses attempted a given number of credit hours. If they earned those credit hours, then they can be considered to have succeeded – no matter their grade. It would not matter if the student received and A or a C, they would have earned the credits that they set out to earn at the beginning of the semester. As a measure of success, then, this study used the percentage of credit hours earned versus credit hours attempted. Although not completely eliminating course difference issues in the analysis, it helped to minimize the impact of the effect on GPA where some courses might be considered to be more difficult or challenging than others.

At Risk

From a long-term institutional perspective, retention, progression, and graduation of students is paramount and has been increasingly elevated under performance-based models of funding (Kantrowitz, 2016). This elevation can come at the expense of providing access to higher education to those who might benefit from it the most. However, at a very high level, at risk students can be defined as those who have a lower chance, based on a number of academic and socio-economic factors, of staying in college and completing their degree.

The academic and admissions processes at most colleges defines these types of at risk students as they enter. Remedial, co-requisite courses, and bridge programs are assigned to incoming students based on their standardized test scores, their high school GPAs and other various factors (Alas, Anshari, Sabtu, & Yunus, 2016). At risk students are identified and categorized as such upon entry.

Colleges and universities also have multiple steps that students can go through to continue their education that are also tied to federal funding. Students who earn lower GPAs are identified and put on academic probation. These students are certainly considered at risk both because they are in danger of losing some or all of their financial aid as well as having a higher chance of dropping out.

These categories of at risk students were important to consider. However, for the purposes of this research, at risk was limited to each semester studied. Because this study used the percentage of credit hours earned over attempted, the operational definition of at risk were those students who were at risk of a lower percentage of credits earned in a given semester. This definition was tied to the requirement for satisfactory academic progress, which requires that students receiving a federal Pell grant "maintain a cumulative grade point average (GPA) of 2.0 or higher and to complete at least two thirds of the course credits they attempt" (Schudde & Scott-Clayton, 2016, p 944). The second part of this requirement served as the foundation for identifying students who might be at risk. For this study, the goal was to test technology-related markers to determine if they could identify students who might be at risk of not earning at least two thirds (or 66%) of the credits they were attempting in each semester analyzed.

Sources

The source for the traditional academic and demographic data was an institution's student information system. The technology-use data came from several places. The institution studied had been collecting wireless network access data, portal login information, and learning management system access via the portal in a separate database. The institution also partnered with a third party for a mobile application that provided data that was extracted into spreadsheet format. All of these sources were used to build the data set.

Population

The population for this research was all students who were enrolled or attempted any classes at one access-based, undergraduate institution during the semesters analyzed. The entire group was disaggregated using academic class and semester with separate analyses performed. Originally, separate analyses were going to be performed on groupings by age, gender, race/ethnicity (White or non-White), first generation status, and co-requisite requirements. However, as the analyses unfolded, none of these groupings indicated sufficient significance to outcomes to investigate separately.

Analysis

The analysis of the data in this research ended up taking three primary forms. First, a descriptive analysis gave some context to work from using two methods. A general description of the population of students for each semester provided for some comparison with future research and between each of the semesters analyzed. In order to test the first hypothesis, all students were split into groups based on individual technology interaction levels. For each of the technology markers tested, if students simply engaged the technology less than twice the number of weeks throughout the semester, they were put into one group while everyone else was put into the other. Descriptive analysis for each group were performed using both term GPA and percentage of credits earned over attempted.

The second set of analyses performed was in preparation for the third set. In order to address possible issues with multicollinearity affecting regression analyses, a correlation analysis was performed. This was done partly to identify the significance of correlations between the dependent variable (percentage of credits earned) and the independent variables. However, the primary purpose of this step was to identify strong and significant correlations between independent variables indicating the duplication of inputs into the regression analyses. Using this method, a portion of the initial set of independent variables were excluded from the next step.

Finally, the third set of analyses testing the second hypothesis was a set of binary logistical regressions. Based on the previously defined threshold of success for this study, students who earned at least 67% of the credits they attempted were assigned a 1, whereas everyone else was assigned a 0. Binary logistical regression was then performed with just the academic independent variables for each semester and for each academic class of students. This was followed by regressions using just technology independent variables. Finally, combining both academic and technology independent variables allowed for comparison between models and testing the second set of hypotheses.

The initial proposal included the development of a technology index by combining technology indicators if they proved to be useful in identifying students. As the analysis progressed, this idea was put aside due to the fact that there were very few independent and significant technology predictors available as shown in next chapter.

The analyses were based primarily on descriptive analysis of groups of students and binary logistic regressions. Only students who had all of the required data were included. Due to the reasons mentioned previously, the dependent variable in the regression analyses was transformed into a binary variable based on the percentage of credit hours earned over credit hours attempted (PCHE).

The following is a list of variables included in the dataset, not all of which were used in the final regressions as determined by the correlation analysis.

HSGPA = High school GPA

FI = Freshman Index (based on SAT/ACT scores)

AClass = Academic class (freshman, sophomore, junior, senior)

FG = First Generation status (first generation, not first generation, unknown)

CCGPA = Cumulative college GPA at the beginning of the semester

CH = Credit hours being taken

HS = Housing status

Pell = Pell Grant recipient

MBS = Merit based scholarship (HOPE or Zell Miller) recipient

CoReq = Co-requisite status

WC = Wireless connections

CPL = Campus portal logins

LMS = Learning management system clicks to enter

MA = Mobile application registration

GEN = Gender

RE = Race/ethnicity (White or non-White)

AB = Age bracket (traditional 18-22 or nontraditional)

Research Data

Demographics

Descriptive demographic information about students was collected and included a few variables. Gender was recorded as male (0) or female (1). Race/ethnicity was recorded and coded in dichotomous form as either White (0) or non-White (1). Age was also transformed into traditional college age (up to 23 years old as 1) or nontraditional (over 23 years old as 0).

Academic Class

For the purposes of this study, students were coded into one of four possible classes. Students who had not yet earned 30 credit hours were coded as Freshman. Students who had earned at least 30 credit hours but had not yet earned 60 credit hours were coded as Sophomores. Students who had earned at least 60 credit hours but had not yet earned 90 credit hours were coded as Juniors. Finally, students who had earned at least 90 credit hours were coded as Seniors.

First Generation Status

The college in the study attempts to determine whether an incoming student is the first in their family to attend college. If both the parents and grandparents of an incoming student have never attended college at any time, then the student is recorded in the database as being a first-generation student. For the entire population of students, first generation status was coded as first generation, not first generation, or unknown.

High School Grade Point Average

For nearly all students, a complete high school transcript with a final GPA is required as part of the admissions process. The only exceptions to this are for nontraditional (older) students who have been out of school for at least 5 years. The high school GPA (HSGPA) established in the data set was their final reported result.

Standardized Test Scores (SAT or ACT)/Freshman Index (FI)

For the institution studied, students entering college must have supplied their scores on either the SAT, historically known as the Scholastic Aptitude Test, or the ACT, historically known as American College Testing. Both test scores were not required, just one or the other. For the purposes of this research, then, the combined SAT or combined ACT scores were used in the analysis. The University System of Georgia uses two formulas for calculating a freshman index (FI) so that all students can be compared no matter their choice of standardized test. Currently new SAT scores are converted to old SAT scores and the FI is calculated as 500 x (HSGPA) + old SAT Critical Reading score + old SAT Math score. For students who submit the ACT, the formula is 500 x (HSGPA) + (ACT Composite x 42) + 88.

College Cumulative Grade Point Average

The cumulative GPA for all college credits earned at the beginning of the semesters being studied was also used as a predictor of future expectations. If students happen to have had no prior college credits, then it was assumed that they were first time freshman and were analyzed as part of that group.

Student Course Load

Many students were full time, but at an access-based institution that is still a majority of commuting students, there were a number of students who were taking only 1 or 2 courses. In order to account for this, the technology predictors used in the regression analysis were divided by the number of credit hours that the student was taking.

Housing Status

The housing status of a student was coded into a dichotomous variable to indicate if the student is living on campus (1) or not (0).

Pell Grant Recipient

Also coded into a dichotomous variable to indicated if the student was a Pell grant recipient (1) or not (0). The Pell grant is based on family financial need.

Zell Miller or HOPE Grant recipient

Coded into a dichotomous variable as well to indicate if the student was a recipient of either the Zell Miller grant or the HOPE grant. Both of these grants are based on academic merit and would be indicative of past academic success.

Corequisite Requirement Status

When students are admitted into the college, their standardized test scores (either ACT or SAT) are evaluated for math or English deficiencies. Based on that analysis, students may be required to take corequisite courses in addition to the standard first semester math and English courses. These students would typically be considered less prepared for college level academic work and as a result, need supplemental instruction to bolster their chances of success in the first-year curriculum. This variable was also dichotomous and indicated a student was either required to take corequisite courses (1) or not (0).

Wireless Network Access

Students who use the wireless network at the college in this study have to log in using their college assigned credentials. If a student showed up on any wireless access point across campus, then a single access was counted in this variable. If a student moved from one building to another, and they appeared on a different wireless access point, then an appearance was added to this variable.

It is important to note that wireless access in the residence halls was not included in this analysis. Only data from access points outside of living areas was available and included in this research. Also, no specific data were collected as to the application in use, the destination or internet traffic on wireless appearances. This variable only includes the number of times a student appeared on the wireless network outside of the residence halls.

Campus Portal Logins

Every time a student logs into the campus portal, no matter where they are in the world, the login is recorded. These logins were coded on a straight one-to-one basis.

Learning Management System Entry Clicks

When a student accesses the learning management system for hybrid or fully online courses through the portal, that act is recorded. The learning management system in use at the college being studied is Brightspace made by D2L, historically known as Desire 2 Learn. D2L can be accessed in other ways, but students use the portal as the primary way to connect into their online course work. Every time a student clicked through the portal into D2L, it was added as a single instance into this variable.

Mobile Application Registration

The institution being studied has partnered with a third party for development and maintenance of a mobile application. The application holds download and registration data for the mobile application as part of their dataset.

The mobile application was so new at the time of this research that institutional programming had not yet been able to take significant advantage of electronic sign-in to events for engagement purposes. For the purposes of this study, this initial variable was dichotomous. Either the student had downloaded and registered with the mobile app (1) or they had not (0).

Chapter IV

RESULTS

This chapter presents the results of the analysis of three semesters of data including two 16-week semesters and one 8-week semester. The Fall 2019 semester was used for the initial and primary analysis due to the higher concentration of first-time, full-time freshman. It is worth noting that individual students might be present in all three datasets. However, each was extracted without identifying data in distinct procedures and there was no intention of tracking students across datasets. Therefore, each dataset is treated and analyzed separately. Also, please note that the following analysis is not presented in chronological order. Instead, Fall 2019 semester data is presented in each section, followed by Spring 2019 and finally, Summer 2019. General descriptive statistics and a preliminary descriptive analysis by raw technology markers is followed by a correlation analysis. Finally, binary logistic regression models and analysis is presented.

Population Description

Fall 2019

For the Fall 2019 semester, records extracted included 2,495 students attempting an average of 12 credit hours. Those without a recorded high school GPA were not included as well as those students who were not at least 18 years of age. For the students in the data set, the mean high school GPA was 3.04. Of the entire population of students, 1,568 had submitted SAT scores with an average total score of 942.84 and 1,027 had submitted ACT scores with an average composite score of 19.57.

Of the students in the dataset, 20% (n = 488) were known to be the first in their respective immediate families to attend college, or what is referred to as first-generation students. Seventy percent (n = 1,748) were not first-generation students and 10% (n = 259) were unknown regarding first-generation status. This group was 69% (n = 1,709) female and 31% (n = 786) male. Sixty-three percent (n = 1,568) of students identified as White whereas 37% (n = 927) were non-White.

Students in this dataset were 22% (n = 551) a nontraditional age (over 23) for undergraduate college students whereas 78% (n = 1,944) where 23 or younger. Forty-two percent (n = 1,059) had received a Pell (need based) grant and 28% (n = 699) were recipients of the HOPE (merit based) grant. Given the combination of high school GPA and SAT or ACT scores, 20% (n = 502) of students were required to take math co-requisite courses in addition to the core curriculum whereas only 9% (n = 231) were required to take English co-requisite courses. Corequisite courses are prescribed to assists students who may not be academically prepared for the core curriculum required math and English courses. 564 (23%) of these students lived in campus housing.

For freshman students, 37% earned less than 67% of the credits they attempted, or the threshold indicating satisfactory academic progress (SAP). For sophomore students, those not making SAP dropped to 13%. Juniors improved to 10% and for seniors, only 6% were not successful.

Spring 2019

For the Spring semester, records extracted included 2,423 students also attempting an average of 12 credit hours. For these students, the mean high school GPA was 3.05. 1,508 students had submitted SAT scores with an average total score of 944.84 and 1,024 students had submitted ACT scores with an average composite score of 19.83.

For the Spring students, 19% (*n* = 448) were known to be first-generation students, 68% (*n* = 1,657) were definitely not first-generation students and 13% (*n* = 318) were unknown regarding first-generation status. This group of students was 67% (*n* = 1,626) female and 33% (*n* = 797) male. Sixty-four percent (*n* = 1,543) of students identified as White whereas 36% (*n* = 880) were non-White.

Spring students were 22% (*n* = 542) a nontraditional age (over 23) for undergraduate college students. Forty-five percent (*n* = 1,097) had received a Pell (need based) grant and 32% (*n* = 779) were recipients of the HOPE (merit based) grant. Twenty percent (*n* = 484) of students were required to take math corequisite courses in addition to the core curriculum whereas 11% (*n* = 268) were required to take English corequisite courses. Finally, 536 (22%) of these students lived in campus housing.

For freshman students, 37% did not make satisfactory academic progress (SAP). For sophomore students, those not making SAP dropped to 15%. Juniors improved to 14% and for seniors, 10% were not successful.

Summer 2019

For the Summer 2019 semester, which is half the length of the other semesters (8 weeks instead of 15 weeks), records included 988 students attempting a lower average of 6 credit hours. For these students, the mean high school GPA was slightly higher than students in the fall and spring semesters at 3.07. Students who had submitted standardized test scores had an average total SAT score of 946.45 and average ACT composite score of 20.04.

For the summer students, 18% (n = 183) were known to be first-generation students, 67% (n = 661) were definitely not first-generation students and 15% (n = 144) were unknown regarding first-generation status. This group of students was 70% (n = 690) female and 30% (n = 298) male. Sixty-three percent (n = 622) of students identified as White whereas 37% (n = 366) were non-White.

Summer students were 29% (n = 287) nontraditional age (over 23). Forty-four percent (n = 430) had received a Pell (need based) grant and 31% (n = 306) were recipients of the HOPE (merit based) grant, 18% (n = 173) were required to take math corequisite courses in addition to the core curriculum whereas 11% (n = 105) were required to take English corequisite courses. Finally, 68 (7%) of these students lived in campus housing.

For freshman students, 18% did not make satisfactory academic progress (SAP). For sophomore students, those not making SAP dropped to 12%. Juniors not making SAP dropped to 10% and for seniors, 11% were not successful.

Overall, the Fall and Spring semesters were similar across all demographics whereas the Summer semester was unique. Due to the shorter semester format, students attempted only half of the average credit hours and were much more even in terms of satisfactory academic progress. Compared to the fall/spring semesters, in the summer, far fewer students live in campus housing, and a higher percentage are female.

Descriptive Analysis

The primary focus of this research was to explore the possibilities of using basic technology interaction or engagement data to identify students who might be at risk of not maintaining satisfactory academic progress, earning at least 67% of the credits they are attempting in any given semester. The first test involved selecting students based on a given technology use threshold for each of the major technology interactions being tested.

For each semester of data, the students were split into groups based on one technology interaction alone. The threshold was chosen based upon the number of weeks in the semester being analyzed. The first test was based on the number of times students appeared on the wireless network over the entire semester with a threshold of 30 (at least twice per week of the semester) for Fall and Spring semesters and 16 for the Summer semester. Once broken into groups, descriptive statistics were run for each group to include their resulting term GPA and the percentage of credits earned which allows for comparison of those below the threshold to those above the threshold.

Once wireless network appearance counts were completed, the number of times students logged into the campus portal was used to group the students using 30 and 16 as the thresholds for the full and Summer semesters respectively. After portal logins, the number of times students entered the learning management system, D2L (Desire 2 Learn) via the portal was used for the same purpose using the same thresholds. Finally, the same set of analyses were performed on each level of student progress or academic classes commonly known as freshman, sophomore, junior and senior.

In nearly every one of these basic analyses, the result was that those who fell below the threshold of twice per week or less had lower average resulting term GPAs and earned a lower percent of the credits they attempted to when compared directly with the group of students who were above the threshold. This was true no matter which technology was used to establish the groups of students. Although not necessarily a causal relationship, these results clearly indicate that technology engagement can be effective as an indicator. A full list of the tables resulting from the descriptive analysis can be found in Appendix A.

Wireless

For the fall term using all academic classes, wireless users who appeared on the network more than twice per week had an average of 0.32 points higher resulting term GPA and percentage earned credits increased by 12%. For freshman only, the difference was higher at an average of 0.44 higher term GPA and 16.9% better average of percentage earned. Sophomore students added 0.16 to their term GPA and percentage of credits earned increased by 6%. Juniors added 0.4 to GPA and 10% to percentage of credits earned. Seniors added only 0.02 to their term GPA, but still increased their percentage of credits earned by 5%. See Figure 1 for an overview of the indicative effect that wireless appearances had for the fall semester on the percentage of credits earned by academic class. This figure clearly demonstrates improvements in every category, but that the difference is the greatest for those in the freshman class. A summary for all terms and all students can be seen in Table 1.

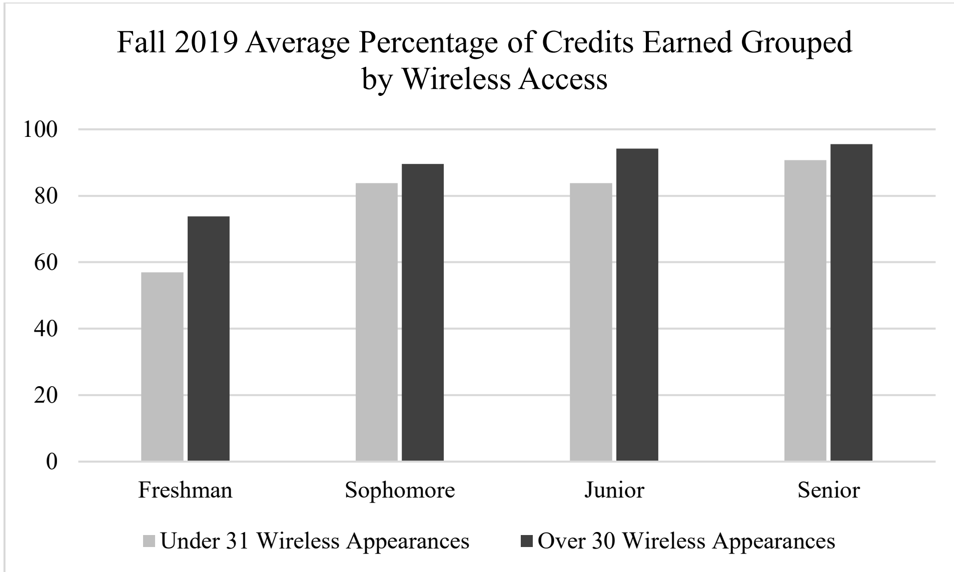

Figure 1. Percentage of credits earned by wireless appearance

The same pattern was evident in the spring term. For all classes, users who appeared on the wireless network had an average of 0.2 points higher term GPA and increased their percentage earned by 8%. The only anomaly was with the freshman class who experienced a slightly lower term GPA but still showed an increase in percent of credits earned of 7%. Sophomore students had an average of 0.13 points higher GPA and 4% higher percentage earned. Juniors averaged 0.21 points higher GPA, with 6% better percentage earned. Seniors earned 0.22 points higher GPA and increased percentage of credits earned by 9%.

For summer, appearance on the wireless network did not hold to the same pattern. Summer courses are shorter and students took an average of 6 credit hours or, roughly, two courses. Most students, therefore, are part time and not on campus as much as during the full semesters. This is also evident in that for the Fall and Spring semesters, the majority of students were above the twice per week threshold whereas, for the

Summer, the opposite was true. For the Summer semester, wireless access does not appear to correlate with an increase in academic performance.

Table 1

Comparison based on wireless appearance threshold (all students)

	Below threshold term GPA	Above threshold term GPA	Below threshold earned percentage of credits attempted	Above threshold earned percentage of credits attempted
Fall	2.38	2.70	75.21	86.93
Spring	2.49	2.68	76.86	85.46
Summer	3.05	2.89	90.74	90.34

Campus Portal Logins

For the fall term using all academic classes, users who logged into the portal more than twice per week had an average of 0.41 points higher term GPA and percentage earned credits increased by an average of 14%. For those in the freshman classification only, the difference was significantly higher at an average of 0.76 higher term GPA and 27.6% better average of percentage earned. Sophomore students added 0.41 to their term GPA and percentage of credits earned increased by 10%. Juniors added 0.35 to GPA and 9% to percentage of credits earned. Seniors added 0.04 to their term GPA and increased their percentage of credits earned by 5%. Figure 2 shows the differences in the percentage of credits earned by academic class when grouped by the portal login threshold of at least two logins per week of the semester. Once again, the difference in performance is most dramatic for those students categorized as freshman. However, each academic class demonstrated improvement to some degree.

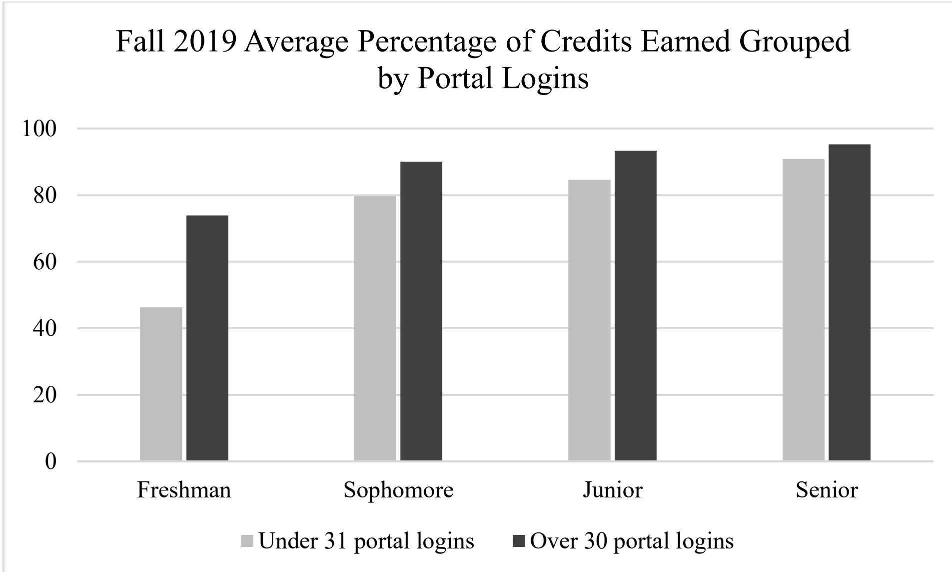

Figure 2. Percentage of credits earned by portal logins

As with wireless, the same pattern for portal logins in the Fall was also found in the Spring term. For all classes, users who logged into the portal more than twice per week had an average of 0.5 points higher term GPA and increased their percentage earned by 14%. The freshman class demonstrated an average 0.5 points higher GPA and an increase in percent of credits earned of 15%. Sophomore students had an average of 0.4 points higher GPA and 14% higher percentage earned. Juniors averaged 0.5 points higher GPA with 11% increase in percentage earned. Seniors earned 0.3 points higher GPA and increased percentage of credits earned by 7%.

Unlike wireless groupings and the summer semester being different, the same is not true when looking at portal logins. On average, students who logged into the portal more than twice per week during the summer increased their GPA by 0.1 and percentage of credits earned by 6%. When divided by academic class, the freshman earned the same GPA, but still managed an average increase of 8% in percentage of credits earned. Sophomore students increased their GPA by 0.2 and increased their percentage of credits earned by 7%. Juniors actually decreased in GPA, but still increased percentage earned by 1%. Seniors increased their GPA by 0.3 points and their percentage of credits earned by 9%. Table 2 summarizes the results for all students in each semester when grouped by the portal login threshold.

Table 2

Comparison based on portal login threshold (all students)

	Below threshold term GPA	Above threshold term GPA	Below threshold earned percentage of credits attempted	Above threshold earned percentage of credits attempted
Fall	2.28	2.69	72.33	86.44
Spring	2.34	2.81	74.73	88.17
Summer	2.94	3.04	86.32	93.00

D2L Access

For the fall term using all academic classes, users logged into the learning management system (D2L) more than twice per week had an average of .3 points higher term GPA and percentage earned credits increased by an average of 10%. For those in the freshman classification, once again the difference was significantly higher at an average of 0.82 increase in term GPA and 29.3% better average of percentage earned. Sophomore students added 0.42 to their term GPA and percentage of credits earned increased by 9%. Juniors added 0.16 to GPA and 1.3% to percentage of credits earned. Seniors actually held steady for term GPA and their percentage of credits earned. Figure 3 shows the difference between group performance for each academic class of student when grouped by logins to the learning management system. The improvement for those in the Freshman class once again stands out from the other classes.

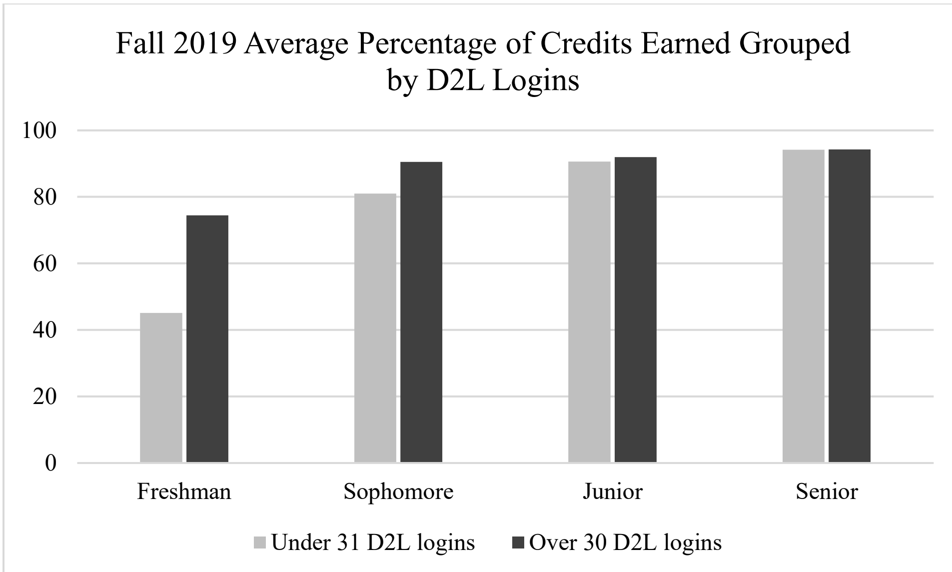

Figure 3. Percentage of credits earned by D2L logins

The same pattern was, again, evident in the spring term. For all classes, users who logged into D2L more than twice per week had an average of 0.4 points higher term GPA and increased their percentage earned by 12%. The freshman class demonstrated an average 0.62 points higher GPA and an increase in percent of credits earned of 16%. Sophomore students had an average of 0.4 points higher GPA and 12% higher percentage earned. Juniors averaged 0.2 points higher GPA with 6% increase in percentage earned. Seniors earned 0.1 points higher GPA and increased percentage of credits earned by 4%.

On average, students who logged into D2L more than twice per week during held steady for term GPA and increased their percentage of credits earned by 4%. When divided by academic class, the freshman earned the same GPA, but managed an average increase of 4% in percentage of credits earned. Sophomore students increased their GPA by 0.2 and increased their percentage of credits earned by 7%. Juniors decreased in GPA, but still increased percentage earned by 2%. Seniors increased their GPA by 0.1 points and their percentage of credits earned by 4%.

Table 3

Comparison based on D2L login threshold (all students)

	Below Threshold Term GPA	Above Threshold Term GPA	Below threshold earned percentage of credits attempted	Above threshold earned percentage of credits attempted
Fall	2.37	2.69	76.20	86.03
Spring	2.35	2.79	75.12	87.60
Summer	2.98	3.02	87.60	92.15

Descriptive Analysis Result

This simple descriptive analysis highlights several important attributes of attempting to use basic technology engagement as an indicator of student success. First, it does appear that basic engagement with technology can indeed be an indicator of students who are more successful. Given the type and format of the semester being analyzed, wireless network logins appear to have some indicating properties outside of the shorter summer semester.

However, at a given threshold of interaction, both portal logins and D2L logins appear to show strong promise as indicators of more successful students. This is especially true for those in the freshman class and even stronger for the fall semester. The fall semester is the traditional starting semester for college and typically has a higher concentration of freshman who have never been in college prior to the start of the term.

Also, although it certainly will vary by institution, the college that provided the data for this analysis schedules nearly all freshman into the same core curriculum courses in the first semester.

This may have a bearing, at least in part, on why these measures are much stronger for those in the freshman class. After the freshman year, the curriculum becomes much less homogenous.

Correlation Analysis

Before moving on to regression models, a correlation analysis of the original variable list was performed to combat multicollinearity in the resulting models. *Multicollinearity* is a term used to describe what happens when two or more independent variables in a regression model have a high degree of linear correlation between each other (Midi, Sarkar, & Rana, 2010). This can skew the results of a model by inadvertently repeating independent factor inputs into a model.

In this research, some of the data points were calculated using some of the other data points. The assigning of math corequisite courses to a student, for example, is a function of the math placement index (MPI). The MPI is calculated from the high school GPA and standardized test scores, such as the ACT or SAT. Adding all of these predictors into a regression model would affect the results because one predictor is calculated from another. In fact, for the fall semester, high school GPA correlates with math placement index at $r(973) = .93$, $p < .001$. Because these are highly correlated (near perfect), both of these independent variables should not be used in the regression model.

The correlation analysis was completed using the fall 2019 student dataset. The first set of correlations performed were between percentage of credits earned (the dependent variable) and each of the original intended predictors (independent variables). Table 4 lists the results of correlations with the dependent variable in order of strength. College GPA prior to the start of the semester had the strongest relationship at $r(2121) = .31$, $p < .001$ followed by high school GPA and the math placement index. Wireless, portal and D2L logins were in the top 10 and all of them were significant with $p < .001$. Age, first generation status and English corequisite did not correlate with percentage of credits earned at a significant level.

Testing the independent variables for multicollinearity, there were many correlations identified, some with very strong relationships, at the two-tailed significance level, all with $p < .001$. The strongest relationships were between high school GPA and English placement index, $r(574) = .96$; math placement index and English placement index, $r(436) = .94$; and high school GPA and math placement index, $r(973) = .93$. These results indicate a nearly perfect correlation and a removal of both the math placement index and the English placement index from regression models.

The next strongest correlation was between portal logins and D2L logins with $r(2493) = .86$, $p < .001$. Entry into D2L is accomplished through the campus portal. This strong relationship means that one of these measurements should be removed from the regression model or combined into a single independent variable.

Table 4

Correlation with percentage of credits earned/attempted for Fall 2019

	Percentage of credits earned/attempted
College GPA	$r(2121) = .31, p < .001$
High school GPA	$r(2493) = .21, p < .001$
Math Placement Index	$r(973) = .19, p < .001$
D2L logins	$r(2493) = .18, p < .001$
HOPE	$r(2493) = .18, p < .001$
Portal logins	$r(2493) = .18, p < .001$
English Placement Index	$r(574) = .17, p < .001$
ACT composite	$r(1025) = .16, p < .001$
Wireless total	$r(2493) = .15, p < .001$
SAT total	$r(1566) = .13, p < .001$
Math corequisite	$r(2493) = -.09, p < .001$
Race	$r(2493) = -.087, p < .001$
Housing	$r(2493) = -.07, p < .001$
Mobile	$r(2493) = -.06, p = .003$
Pell	$r(2493) = -.04, p = .037$
Sex	$r(2493) = .04, p = .042$
Hours attempted	$r(2493) = .04, p = .045$
Age	$r(2493) = -.04, p = .052$
First generation status	$r(2234) = -.04, p = .099$
English corequisite	$r(2493) = -.03, p = .101$

Additional strong and significant correlations were identified between SAT total and ACT composite scores, $r(409) = .78$, $p < .001$; English placement index and English corequisite status, $r(574) = -.52$, $p < .001$; math placement index and math corequisite status, $r(973) = -.49$, $p < .001$; HSGPA and ACT composite score, $r(1025) = .48$, $p < .001$; HSGPA and HOPE Grant, $r(2493) = .48$, $p < .001$; and HSGPA and SAT total score, $r(1566) = .46$, $p < .001$.

Several of these results indicated that elimination of independent variables was in order. Specifically, the math and English placement indexes, the math and English co-course requirements, the merit-based scholarship (HOPE) and age bracket were all determined to be duplicate inputs to regression models in multiple ways. Further, it was determined that high school GPA and standardized test scores should not be used together in the same model.

In order to determine which of these measures to include in the regression analysis, a single linear regression for each was performed using the fall semester data with the resulting term GPA as the dependent variable. For those who had recorded SAT scores, both the SAT total score and high school GPA were found to be significant. However, the results demonstrated that high school GPA was a stronger indicator of success. For SAT total score, TermGPA = 0.83 + 0.002(SATTotal)*, with an $r^2 = .06$. For high school GPA, TermGPA = 0.37 + 0.73(HSGPA)*, with an $r^2 = .11$.

Similarly, for students who had recorded ACT scores, both the ACT composite score and high school GPA were found to be significant. The results also indicated the high school GPA was the stronger predictor. For ACT composite score, TermGPA =

0.70 + 0.094(ACTComp)* with an $r^2 = .09$. For high school GPA, TermGPA = 0.38 + 0.81(HSGPA)* with an $r^2 = .12$. With the further complication that all students in the data sets had high school GPAs whereas only some had SAT scores or ACT scores, it was decided that high school GPA would be included in the regressions and standardized test scores would be eliminated.

Regression Analysis

For the regression analysis, percentage of credits earned was transformed into a dichotomous variable based on the federal definition of satisfactory academic progress in order to continue to receive financial aid. If students were awarded at least 67% of the credits that they attempted, then the new variable of PerEarned67 was coded as a 1. The students who were awarded less than 67% of the credits they attempted were coded as a 0. Using this method allowed for a binary logistic regression analysis. Students were either successful or not.

Also, even though credits attempted were included in the appropriate regression analyses, it was necessary to transform the technology-related variables. Students took a certain number of courses over the same length of time, but not all students took the same number of courses. Dividing the technology counts by the number of credit hours attempted allowed for processing of students on a level field. Students who only attempted one course would naturally be engaging less than others who attempted five courses, for example. For this reason, wireless counts, portal logins and D2L logins were transformed into WirelessPATT, PortalPATT and D2LPATT respectively where PATT stands for Per hours ATTempted. A full list of the tables resulting from the regression analysis can be found in Appendix B.

Regressions Without Technology Variables

The first set of regression analyses done was with academic independent variables only. Results of the regression using all students is followed by individual regressions for freshman, sophomore, junior and senior students. Independent variables used included high school GPA (HSGPA), college GPA (ColGPA) for all students except the freshman class, credit hours attempted (HrsAtt), need based grant (Pell), campus housing (Housing), Race (White = 0, All others = 1), gender (Sex) (Male = 0, Female = 1) and first-generation status if known (not first-generation = 0, first-generation = 1).

For the fall semester using all students, the results showed that

The predicted logit of (PerEarned67) = -2.62 + (0.44)*HSGPA + (0.90)*ColGPA + (0.05)*HrsAtt + (-0.11)Pell + (0.08)Housing + (-0.07)Race + (0.16)Sex + (0.13)FG.

In this model, the log of the odds of a student earning at least 67% of their attempted credits was positively related to their HSGPA ($p = .002$), positively related to ColGPA ($p < .001$) and positively related to HrsAtt ($p = .02$). Pell status, housing status, race, sex and first generation were not significant in this model. The likelihood ratio test of this model is 192.03 ($p < .001$) with a Nagelkerke $R^2 = .17$. The Hosmer and Lemeshow (H-L) test indicated a pass for this model with $p = .86$. An H-L test that shows insignificant results indicates a good model fit (Peng, Lee & Ingersoll, 2002). Finally, the Concordance Index (c-statistic) for this model was .74. Models with a higher c-statistic indicate better performance in assigning probabilities to outcomes based on given observations. (Peng et al., 2002).

Therefore, it appears this model is significant and fits the data being analyzed. The odds ratio, or Exp(B) for each of the significant independent variables indicates that a one unit increase in high school GPA, for example, increases the probability of that student being successful by 54.5%. Likewise, a 1 unit increase in college GPA increases the probability (according to this model) of achieving at least 67% of the hours attempted by 108%. Finally, a 1 unit increase in the credit hours attempted increases the probability of success by 0.7%.

For the fall freshman class, the significant variables shifted to (.94)*HSGPA, $p <$ .001 and (-.34)*Race, $p = .045$. College GPA was not used and hours attempted fell out of significance. Nagelkerke R^2 was .09 and the c-statistic was calculated to .66 for the freshman class.

For the sophomore class, the significant variables shifted once again to (.89)*ColGPA, $p < .001$ and (.54)*Sex, $p = .024$. No other variables were significant. Nagelkerke R^2 was .11 and the c-statistic rose to .71 for the sophomore class.

Only college GPA was significant for the junior class at (1.26)*ColGPA, p = .001. N-R^2 = .10 and the c-statistic came in at .72 for juniors. Seniors had no significant predictors among the variables used in this model. None of the academic class level regressions demonstrated issues with the H-L test, indicating that the models fit the data.

For the Spring semester, the all student regression followed the same pattern as for Fall.

The predicted logit of (PerEarned67) = -3.57 + (0.56)*HSGPA + (1.02)*ColGPA + (0.07)*HrsAtt + (-.002)Pell + (0.07)Housing + (-0.14)Race + (-0.13)Sex + (-0.09)FG.

HSGPA, ColGPA, and HrsAtt were all significant with $p < .001$. The overall model N-R^2 = .22 and the c-statistic came in at .77. These are very similar to the Fall results, though slightly stronger. Unlike Fall, however, the H-L test indicated a problem with data fit with $p = .01$. This issue carried through to the freshman class, but not the other classes.

For the Spring freshman class, only HSGPA was significant at (1.10)*HSGPA, $p < .001$. N-R^2 = .10 and the c-statistic = .66 for the freshman class. However, the H-L test was significant with $p = .004$ indicating an issue with model fit.

Sophomore results shifted back to (0.96)*ColGPA, $p < .001$ and (0.11)*HrsAtt, $p = .001$ as the only significant independent variables. In this case, N-R^2 = .14 and the c-statistic was .74. The H-L test was not significant for sophomores, juniors or seniors.

For junior students, (0.86)*ColGPA, $p = .027$ and (-0.81)*Race, $p = .01$ were the significant predictors. The junior model resulted in N-R^2 = .16 and a c-statistic of .74. Seniors move back to (3.134)*ColGPA, p < .001 and (0.214)*HrsAtt, p = .001 as the significant independent variables. The senior model resulted in N-R^2 = .37 and a c-statistic of .88. These results indicate that the academic only model is very strong for the Spring senior student data.

The Summer all student model only resulted in college GPA as being significant with $p < .001$.

The predicted logit of (PerEarned67) = -0.36 + (0.25)HSGPA + (0.56)*ColGPA + (0.003)HrsAtt + (-0.14)Pell + (-0.18)Housing + (-0.20)Race + (0.06)Sex + (-0.10)FG.

The summer all student model N-R^2 = .07 and the c-statistic came in at .67. The H-L test was not significant, but the overall model fit was weaker than for Fall or Spring.

The freshman class model for Summer students did not indicate any significant academic predictors among those used in the model. Sophomore students, however, did indicate (0.91)*ColGPA, $p = .015$ as the single significant predictor. The sophomore model N-R^2 = .12 and the c-statistic = .71.

The Summer junior student, academic model also did not indicate any significant predictors among the independent variables. Senior students followed the same pattern as the sophomore model with (1.82)*ColGPA, $p = .004$ being the only significant variable. The senior model N-R^2 = .14 with a c-statistic of .75.

Non-Technology Regression Findings

Analysis using traditional academic predictors in a binary logistic regression model produced mixed results. The majority of these tests produced a Nagelkerke R^2 between .06 and .20 and a c-statistic between .60 and .79. The single strongest model performance was for the Spring senior students. However, senior students perform at higher levels in terms of satisfactory academic progress, especially in the longer Spring and Fall terms.

Some of the nontechnology regressions indicated that there might be issues with model fit to observed data, but this was generally not the case. Further, it seems clear that college GPA, high school GPA, hours attempted, sex and race were all significant in different groups. Pell or need based grant, housing status and first-generation status were not indicated as significant in any of the nontechnology regression models.

Academic With Technology Regressions

The next step in the analysis was to perform the same set of regressions adding in mobile app registration status, wireless appearance and D2L logins. For the Fall semester using all students then, the results now showed that

The predicted logit of (PerEarned67) = -3.56 + (0.49)*HSGPA + (0.81)*ColGPA + (0.07)*HrsAtt + (-0.13)Pell + (-0.50)Housing + (-0.15)Race + (0.12)Sex + (0.06)FG + (-0.39)*Mobile + (0.08)*D2LPATT + (0.04)*WirelessPATT.

This model with all students for the Fall semester maintained the same three significant independent variables, but added all three technology variables as significant predictors. All three technology variables had $p < .001$. This model improved both the Nagelkerke R2 to .28 and the c-statistic to .81. Unfortunately, the Hosmer and Lemeshow test produced a significant result $p = .013$ where the nontechnology model did not.

However, none of the individual class regressions for the Fall semester produced a significant H-L test result. For freshman, the significant independent variables were (1.10)*HSGPA, (-0.44)*Race, (0.11)*D2LPATT, and (0.03)*WirelessPATT. The N-R^2 improved over the nontechnology model from .09 to .28 and the c-statistic also improved from .66 to .78. Figure 4 shows the significant improvement in the c-statistic by graphing both the academic only and academic plus technology regressions receiver operating characteristic (ROC) curves. The area under the curve results in the c-statistic for each model. The reference line is at .5, which would be essentially the same as the random assignment of the probability of a student succeeding (earning at least 67% of the credits they attempted) based on the given observations (Peng et al., 2002). The more area under the curve, the stronger the model is. The area between the two curves represents the improvement from the non-technology model to the one that includes the technology-related predictors.

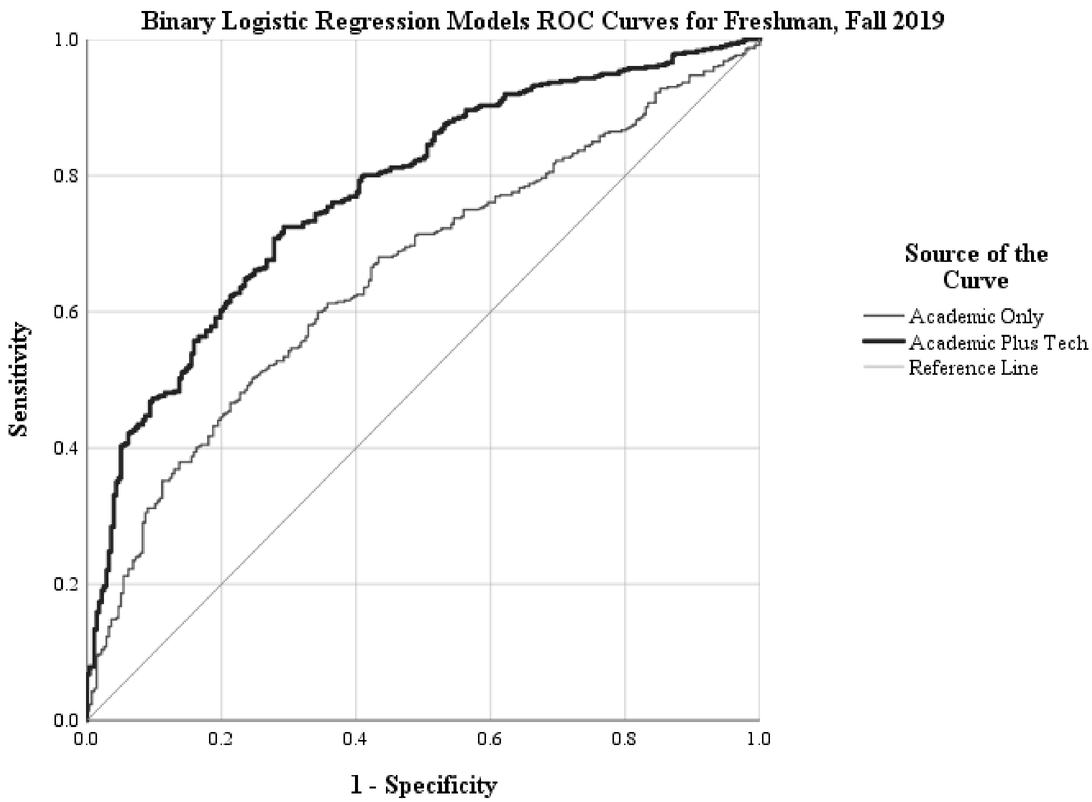

Figure 4. ROC curve improvement for Freshman, Fall 2019

For the sophomore class, the significant variables were (0.77)*ColGPA, (0.54)*Sex, (0.08)*D2LPATT, and (0.02)*WirelessPATT. The N-R^2 improved to .18 and the c-statistic also improved slightly to .76.

Only college GPA and wireless access turned out to be significant for the junior class with (1.14)*ColGPA and (0.04)*WirelessPATT. The junior class N-R^2 improved to .18 as well as the c-statistic which improved to .79.

Fall seniors did not have any significant predictors in the nontechnology model, and added only wireless at (0.057)*WirelessPATT. N-R^2 for the Fall senior class was .22 and the c-statistic was .84.

Unlike the Fall semester, the all student Spring semester regression did not show a significant result with the H-L test. For the Spring semester using all students

The predicted logit of (PerEarned67) = -4.49 + (0.66)*HSGPA + (0.97)*ColGPA + (0.07)*HrsAtt + (-0.10)Pell + (-0.20)Housing + (-0.15)Race + (-0.22)Sex + (-0.17)FG + (0.04)Mobile + (0.10)*D2LPATT + (0.02)*WirelessPATT.

All significant variables had $p < .001$. For the all student regression, the N-R^2 improved to .29 and the c-statistic improved slightly to .80.

For Spring freshman only, the significant variables were (1.37)*HSGPA, (-0.40)*Sex, (0.14)*D2LPATT, and (0.01)*WirelessPATT. N-R^2 improved significantly to .24 and the c-statistic also improved to .75. Unlike the nontechnology Spring freshman regression, the addition of the technology variables did not produce a significant H-L test result indicating a better model fit in addition to the improvements in N-R^2 and the c-statistic. Figure 5 visualizes the improvement in the c-statistic for the Freshman class in the Spring semester as with the Fall semester.

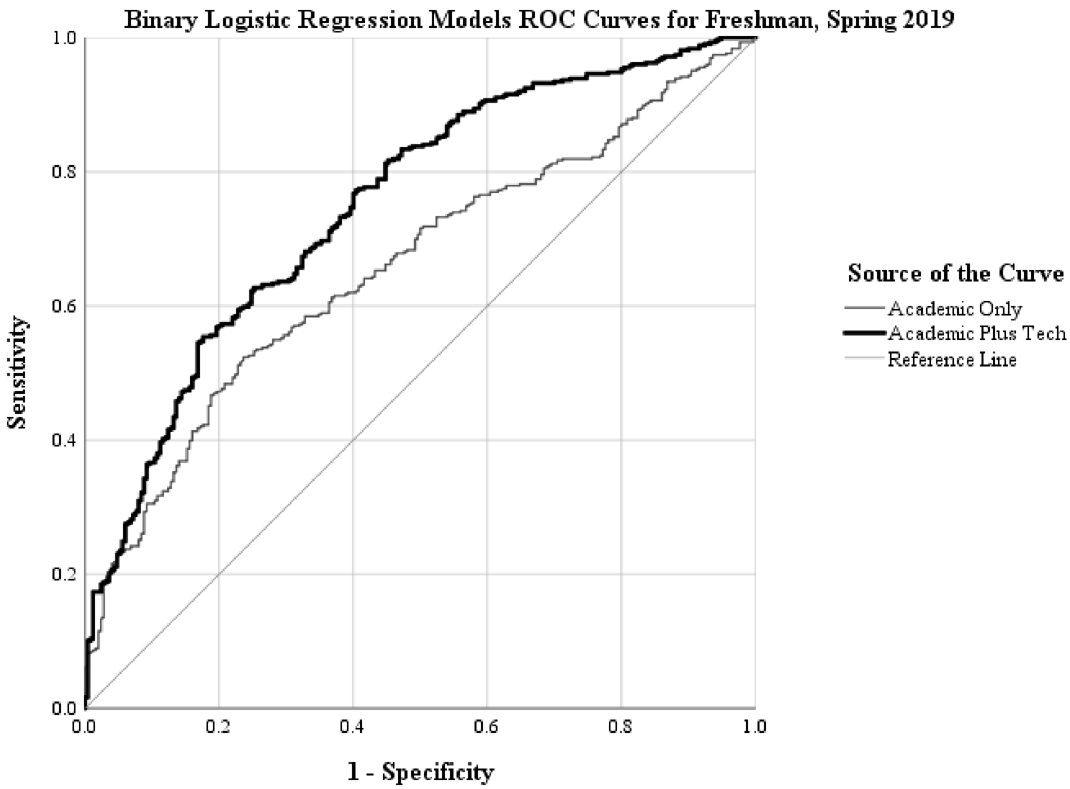

Figure 5. ROC curve improvement for freshman, Spring 2019

For the spring sophomore students, (0.79)*ColGPA, (0.13)*HrsAtt, (0.10)*D2LPATT, (0.02)*WirelessPATT, and (-0.54)*Mobile were all significant variables. The N-R^2 improved to .23 and the c-statistic also improved to .79 over the nontechnology model.

For junior students, (0.81)*HSGPA, (-0.97)*Race, and (0.10)*D2LPATT were the significant predictors. However, in this case, the H-L test was significant indicating that there might be an issue with the model. For comparison, though, the N-R^2 improved to .23 and the c-statistic also improved slightly to .78.

The Spring senior model, though, did not produce a significant H-L test result. The significant variables were (3.14)*ColGPA and (0.21)*HrsAtt, just as with the nontechnology regression. Even though none of the technology variables were significant, the overall model still managed to improve both the N-R^2 (.39) and c-statistic (.89) slightly.

For the summer semester all student regression including technology variables…

The predicted logit of (PerEarned67) = -1.02 + (0.36)HSGPA + (0.54)*ColGPA + (0.01)HrsAtt + (-0.22)Pell + (-0.41)Housing + (-0.15)Race + (0.02)Sex + (-0.15)FG + (0.04)Mobile + (0.05)*D2LPATT + (0.02)WirelessPATT.

None of the Summer semester regressions produced a significant result for Hosmer and Lemeshow tests. The all student model improved slightly for both the Nagelkerke R2 (.10) and the c-statistic (.71).

The freshman class model for summer students had no significant independent variables in the nontechnology model, but did indicate D2LPATT as significant in this model with an N-R^2 of .09 and a c-statistic of .70. Sophomore students maintained only (0.83)*ColGPA as the only significant variable and both the N-R^2 and c-statistic were the same as in the nontechnology model.

For the summer junior class, none of the independent variables were significant. For the senior class, however, (1.84)*ColGPA and (0.23)*D2LPATT were both significant. Further, both the N-R^2 (.28) and c-statistic (.83) improved over the nontechnology model.

Technology Inclusion Regression Findings

The results of performing binary logistic regression analysis on the same data using the same groups with and without basic technology interaction data offers compelling evidence of significant improvements in models. In every single case, the addition of technology predictors to the regression model improved the likelihood ratio, the Nagelkerke R^2, and the c-statistic. Although the Nagelkerke R^2 is not directly comparable to R^2 in linear regression, it can be used as a supplemental indicator of improvement along with other measures, such as the c-statistic and likelihood ratio tests (Peng et al., 2002). Table 6 shows the result of comparing the same regressions without technology (NT) and with technology (WT) using Nagelkerke R^2, likelihood-ratio and c-statistic using the Fall 2019 dataset. In every case using any measure, the models improve with technology predictors added.

Table 5

Regression model comparisons no tech (NT) and with tech (WT) using Fall 2019 student data

	N-R^2 NT	N-R^2 WT	Likelihood-Ratio NT	Likelihood-Ratio WT	C-statistic NT	C-statistic WT
All	.165	.275	192.03	330.95	.741	.810
Freshman	.087	.284	49.07	174.63	.657	.776
Sophomore	.109	.177	41.29	68.785	.713	.760
Junior	.101	.182	21.50	39.435	.719	.786
Senior	.132	.218	13.02	21.677	.793	.840

Analysis of Hypotheses

In Chapter 3, two sets of hypotheses are introduced regarding using basic technology engagement measures to identify college students who might be at risk of not earning at least 67% of the credits they attempt in any given semester. In a two-fold approach, technology engagement measures were looked at alone and then added to traditional academic predictors to see if models improved.

In the first null hypothesis, it was predicted that there would be no correlation between the volume of basic technology engagement and the percentage of credits earned over attempted. To test this hypothesis, students were simply divided into two groups based on each of the technologies being tested and a threshold of 2 times per week of the semester in question. Two semesters were 15 weeks whereas the summer semester was 8 weeks. If a student engaged the technology 30 times or less (for the longer semesters), then they were placed in one group whereas the others were placed in the opposing group. For the next technology being analyzed, all students we sorted in the same way regardless of where they landed in the previous analysis.

When analyzed in this way, in nearly every case, the students who fell below the threshold had a lower average term GPA and a lower percentage of credits earned. This was especially true of Freshman students who exhibited the largest difference between groups when analyzing wireless logins, portal logins or LMS (D2L) logins. The largest of these differences was with D2L logins for the Fall 2019 semester with those above the threshold averaging almost a full point GPA (0.82) higher and a significant 29.3% improvement in credit hours earned.

Although not establishing a causal relationship, the results clearly show that basic technology engagement can indeed be used as an indicator of improved chances for success. Therefore, the results suggest that the first null hypothesis can be rejected and the alternate hypothesis accepted.

The second null hypothesis predicted that when combined with traditional academic performance predictors, technology engagement by students would not strengthen the predictive model. In order to test this hypothesis, multiple binary linear regressions were performed first with only traditional academic predictors, and then with technology engagement variables added in. The resulting models were compared using Nagelkerke R2, likelihood-ratio tests and the c-statistic. In each and every case, using any of these measures, the models using the technology engagement variables improved over the same models without the technology variables added in. These results suggest that the second null hypothesis can also be rejected and the alternate hypothesis, therefore, can be accepted.

Chapter V

DISCUSSION

Findings

The results of this research indicate that big-data nearly real-time techniques are applicable and may be very useful in identifying students who may be at risk before it is too late to intervene. As the results suggest, these techniques do not necessarily have to be complex or require extreme amounts of processing in order to take advantage of already existing or easily collected data on student behaviors regarding simple engagement with technology.

Simple counting of interactions or engagements with basic technology of wireless access, portal logins and learning management systems is a good place to start. The results of this study suggest that adding these types of measurements to traditional academic predictors significantly improves the ability of the institution to identify students who have a reduced chance of success in any given semester. This is especially true for the newest students attending college, those in the freshman class.

As noted Chapter 2, the previous research using technology engagement as indicative of success is scarce and results are mixed. Some, such as Abdous et al. (2012), studying more synchronous uses of technology between faculty and students, found no correlation between technology activity and academic success. Depending the type of technology and the measures used, however, most of the research indicated significant positive relationships. Kuh and Vesper (1999) established a positive correlation between the use of technology and academic performance. Macfadyen and Dawson (2010) researched learning management system data and were able to correctly identify four out of five of the students who failed the course in the study. In this research, the first hypothesis was confirmed by the analysis and supports much of the previous work in this field.

The second hypothesis was also confirmed in that when simple technology interaction data is combined with academic predictors, the accuracy of the models is strengthened. The closest prior research akin to this type of study was by Aguiar et al. (2014). Using only logins and hits to the electronic portfolio system and combining it with traditional academic predictors, significantly improved on their ability to correctly identify students who dropped the program after the semester was over. This finding matches the confirmation of the second hypothesis in this study.

It is important, however, to use these tools as indicators and not solutions, as there is no established causal relationship. Forcing students to log into the learning management system more often, for instance, will not cause the student to be successful. Observing student behavior via technology, then, is an indicator only. Such tools can highlight students who might be struggling. Using indicators as red flags, as it were, to reach out to faculty, advisors and mentors to discover and intervene, when warranted, can give more students the chance to be successful.

For this study, the results clearly indicate strong correlations between observed technology engagement levels and student success. Further, the combination of traditional academic predictors with technology engagement greatly enhances the ability to flag students who have a lower chance of success with the most significant impact seen earlier in the academic progression.

Study Limitations

As with any study. there are several limitations to be aware of in this case, some of which might be excellent directions for future or expanded research. No distinctions were made in terms of technology interaction between students enrolled in different programs of study. It may be that students in hospitality programs would naturally have much lower interaction with the technology tools being studied than students in the nursing program would have. Further, although credit hours attempted were considered in the analysis, students may have been attempting the same number of hours, but had completely different curriculums. Even the same student may experience completely different levels of success with two different semesters due to many factors, one of which could be differences in the instructors or the courses themselves.

Also, this study was limited based on the assumption that nearly all students carried personal wireless devices and, more importantly, that they connected them to the campus wireless network. Especially because this study was taking place at an institution where access is part of the mission, it may prove to be that many students come from disadvantaged backgrounds and cannot afford their own personal wireless devices (such as cell phones). Students who were enrolled in completely online courses may also have never been present on campus. Further, it should be noted that no data was collected concerning activity beyond appearing on the wireless network. Students logging in my be doing anything with that connection including academic-related work, social networking, gaming or any other applicable activity.

Finally, because this research was at one institution with access as part of its mission, the results may be very specific to that environment. What was discovered through this research may not be generalizable to higher education as a whole. The process and resulting tools may be useful, but future research would need to test the outcomes at both institutions that are access based and those who are decidedly more selective in their admissions process.

Further Research

This study was performed using the most basic technology engagement data at one access-based institution in an effort to test simple and efficient ways to identify students who might be at risk. Although there is significant existing research under the wide umbrella of student engagement and its importance to student success in college, there is little that is focused on technology engagement predictors. There is research around deeper levels of engagement in learning management systems and the rich data that they can provide (Wilson, Watson, Thompson, Drew, & Doyle, 2017). However, all courses are not online or even have a hybrid component.

Additionally, there is research into using technology to engage students in college as a means to foster affiliation, increase communication and help students transition into college to be successful (Rowan-Kenyon, Mart nez Alem n, & Savitz-Romer, 2018). However, students are not all alike and may be successful engaging in different ways. Studies like these are an invaluable part of helping students be successful. Their efforts concentrate on ways to intervene with students as a whole. The aim of this study was to quickly and simply identify students who are struggling so that intervention strategies can be timely, tailored and targeted.

Verification and Expansion

Further research would be important to test the conclusions of this study both at access based and more selective institutions, but also to expand on possible additional technology engagement measures. In addition to wireless access, campus portal logins and learning management system logins, many campuses use additional tools, some that are specific to gauging student engagement. It may be that some of these other technologies are also easy to measure and just as effective at enhancing predictive models.

Mobile applications specific to the college or university may be more applicable than what was seen in this study. The mobile application at this institution was still relatively new and although used by a good number of students, had not been fully adopted and integrated into campus life. Other colleges may have a more mature application used by students, faculty and staff on a regular basis.

Deeper Analysis

Although this study was records based only, a simple interactive study might be as effective and shed new light in other areas. Using technology to survey all students quickly and efficiently could be very useful. At the college in this study, the capability exists to pop-up a short survey after logging in and, in effect force students to fill it in before they can access anything else through the portal. Texting students questions is also another way to develop an interactive study.

Additionally, this study was blind to the individual student, did not track progress, or look at individual courses that students attempted. Performing analysis of technology engagement and success by course or at the very least, program of study could also yield some incredibly helpful insights.

Learning communities should also be considered for a deeper study. Comparing student technology engagement between those who are in the same learning community, if they exist at a given institution would also be very useful information. Students who have the same schedule, taking the same classes from the same professors at the same time provides a level basis for comparison. Individual demographic information added to those in a learning community to test engagement levels might be possible at the right institution.

Wireless Tracking

The wireless login database used in this study includes access point information, although it was not extracted in the datasets. Knowing which students appeared on which access points at what times might also be a good starting point for a future study. Do students spend time in the library? Do they show up for class? What peers are consistently showing up at the same time on the same access points? Is a given student always around the same group of students or is their peer group constantly shifting? All of this is possible to determine from a managed wireless network and algorithms for scoring students on technology engagement could be developed.

Additionally, it is conceivable that a deeper tracking of wireless activity, such as application in use or general network traffic categories could be implemented. Such information could then be analyzed in combination with other factors to see if activity type might be used as indicative of student engagement in campus life and academic activities.

The Next Step: Intervention Strategies

The next logical step in helping students succeed once they are identified is to develop and evaluate intervention strategies. Students flagged automatically through an early alert effort may not, in fact, be struggling or at risk. Working with faculty and other advisors close to the student to successfully verify they are at risk will be an important step as well. Future study might take either of these directions and expand on the wealth of research already existing on student intervention strategies.

Driving deep into individualized and even automated ways to intervene is also a growing field of study. If we know that students taking a particular course, for instance, demonstrate trouble in one of four ways, then identifying the manifested trouble is one way to individualize the response. Defining a few effective strategies for intervention specific to the issue and the type of student based on demographic or prior academic markers can produce a tailored solution to give that student the highest chance of success. Studies in this direction would be excellent for future research.

Conclusion

Colleges and universities face uncertain times more than ever and must find ways to help students succeed. As more scrutiny is placed on the return on investment for a college education from all levels, erratic enrollment patterns, volatile politics and economics force long standing practices to be altered or at least challenged and refined.

This study confirms that there are yet untapped methods to quickly and easily identify students who might be struggling in an effort to do so before it is too late to truly help them be successful. Vast amounts of possibly unused data is available and waiting for colleges to combine with traditional academic data to find new ways to generate insights into student engagement. The good news, as the results of this study suggest, is that the capture, analysis and integration of this valuable data does not have to be extremely complex.

In this study, the technology engagement data was simple counts of interaction, or logins. With relatively straight-forward preparation, this type of data can be analyzed in near real-time, or at the very least, on a weekly basis. If colleges can automate the flagging of students based on observational data instead of waiting for faculty or advisors to notice an issue, then the needle can be moved from the reactive side towards the proactive side.

To be certain, there is no perfect solution when predicting student outcomes, but this is a step in the right direction. Most importantly, the techniques used in this study appear to be the strongest for those in the Freshman class. Although it may not be applicable for every type of institution, for access-based colleges, helping Freshman students to transition into college and be successful is paramount. For the institution in this study, the Freshman class is the largest group of students enrolled. With academic class, the group becomes smaller. There are fewer Sophomores than Freshman students, fewer Juniors than Sophomores, and so on.

If we can increase the base of students in the Freshman class by helping them to be successful, then more students will progress–hopefully, all the way to graduation. This scenario would improve the overall performance of an institution and begin to demonstrate returns for those scrutinizing higher education.

However, helping students find success in college is more than about proving performance, or even return on investment. It is simply the right thing to do. Faculty, staff and administrators poor their lives into helping students be successful not to prove that they can, but to improve student's lives. When students win, everyone wins.

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APPENDIX A

Descriptive Analysis Tables

Spring 2019 Semester (15 weeks)

Table 6

All students, wireless total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	724	0.00	4.00	2.4881	1.35450
PerEarned	724	0.00	100.00	76.8587	36.60195

Table 7

All students, wireless total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	1699	0.00	4.00	2.6828	1.07884
PerEarned	1699	0.00	100.00	85.4644	26.50544

Table 8

All students, portal login total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	952	0.00	4.00	2.3352	1.32141
PerEarned	952	0.00	100.00	74.7330	36.17808

Table 9

All students, portal login total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	1471	0.00	4.00	2.8120	1.02022
PerEarned	1471	0.00	100.00	88.1739	24.04615

Table 10

All students, D2L login total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	914	0.00	4.00	2.3515	1.34295
PerEarned	914	0.00	100.00	75.1166	36.45421

Table 11

All students, D2L login total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	1509	0.00	4.00	2.7901	1.01902
PerEarned	1509	0.00	100.00	87.6032	24.39000

Table 12

Freshman class, wireless total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	276	0.00	4.00	2.1134	1.53138
PerEarned	276	0.00	100.00	64.7509	49.96812

Table 13

Freshman class, wireless total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	454	0.00	4.00	2.0995	1.17848
PerEarned	454	0.00	100.00	71.5321	32.56593

Table 14

Freshman class, portal login total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	315	0.00	4.00	1.8090	1.43402
PerEarned	315	0.00	100.00	60.1721	41.58020

Table 15

Freshman class, portal login total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	415	0.00	4.00	2.3292	1.18353
PerEarned	415	0.00	100.00	75.6449	31.48072

Table 16

Freshman class, D2L login total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	313	0.00	4.00	1.7488	1.45187
PerEarned	313	0.00	100.00	59.0341	42.42363

Table 17

Freshman class, D2L login total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	417	0.00	4.00	2.3718	1.14670
PerEarned	417	0.00	100.00	76.4248	30.24094

Table 18

Sophomore class, wireless total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	203	0.00	4.00	2.6215	1.19171
PerEarned	203	0.00	100.00	83.3146	30.87579

Table 19

Sophomore class, wireless total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	524	0.00	4.00	2.7503	0.98745
PerEarned	524	0.00	100.00	87.6198	23.56849

Table 20

Sophomore class, portal login total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	300	0.00	4.00	2.4720	1.21481
PerEarned	300	0.00	100.00	78.2844	32.25191

Table 21

Sophomore class, portal login total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	427	0.00	4.00	2.8845	0.87750
PerEarned	427	0.00	100.00	92.1319	18.19245

Table 22

Sophomore class, D2L login total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	281	0.00	4.00	2.4655	1.21468
PerEarned	281	0.00	100.00	78.8162	32.05397

Table 23

Sophomore class, D2L login total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	446	0.00	4.00	2.8711	0.89665
PerEarned	446	0.00	100.00	91.2069	19.63940

Table 24

Junior class, wireless total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	105	0.00	4.00	2.6585	1.06339
PerEarned	105	0.00	100.00	84.8622	26.21822

Table 25

Junior class, wireless total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	365	0.00	4.00	2.8718	0.97830
PerEarned	365	0.00	100.00	90.5441	22.70708

Table 26

Junior class, portal login total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	166	0.00	4.00	2.5215	1.12230
PerEarned	166	0.00	100.00	82.4042	30.17136

Table 27

Junior class, portal login total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	304	0.00	4.00	2.9894	0.88694
PerEarned	304	0.00	100.00	93.0265	18.12023

Table 28

Junior class, D2L login total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	156	0.00	4.00	2.6928	1.06909
PerEarned	156	0.00	100.00	85.5594	27.34332

Table 29

Junior class, D2L login total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	314	0.00	4.00	2.8894	0.96007
PerEarned	314	0.00	100.00	91.1206	21.35162

Table 30

Senior class, wireless total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	140	0.00	4.00	2.9057	1.22104
PerEarned	140	0.00	100.00	85.3649	30.70477

Table 31

Senior class, wireless total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	356	0.00	4.00	3.1338	0.83326
PerEarned	356	0.00	100.00	94.8512	17.02896

Table 32

Senior class, portal login total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	171	0.00	4.00	2.8836	1.12653
PerEarned	171	0.00	100.00	87.8786	27.73141

Table 33

Senior class, portal login total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	325	0.00	4.00	3.1672	0.85021
PerEarned	325	0.00	100.00	94.4335	18.21380

Table 34

Senior class, D2L login total < 31, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	164	0.00	4.00	2.9819	1.10207
PerEarned	164	0.00	100.00	89.5382	26.24436

Table 35

Senior class, D2L login total > 30, Spring 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	332	0.00	4.00	3.1127	0.88476
PerEarned	332	0.00	100.00	93.4755	19.74639

Summer 2019 Semester (8 weeks)

Table 36

All students, wireless total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	692	0.00	4.00	3.0548	1.09696
PerEarned	692	0.00	100.00	90.7440	24.70703

Table 37

All students, wireless total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	296	0.00	4.00	2.8929	1.07699
PerEarned	296	0.00	100.00	90.3364	24.61217

Table 38

All students, portal login total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	352	0.00	4.00	2.9365	1.24790
PerEarned	352	0.00	100.00	86.3245	30.80703

Table 39

All students, portal login total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	636	0.00	4.00	3.0449	0.99593
PerEarned	636	0.00	100.00	93.0003	20.13038

Table 40

All students, D2L login total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	331	0.00	4.00	2.9830	1.21299
PerEarned	331	0.00	100.00	87.5966	29.20010

Table 41

All students, D2L login total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	657	0.00	4.00	3.0180	1.02803
PerEarned	657	0.00	100.00	92.1460	21.89974

Table 42

Freshman class, wireless total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	163	0.00	4.00	2.7996	1.19671
PerEarned	163	0.00	100.00	86.3690	29.13098

Table 43

Freshman class, wireless total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	61	0.00	4.00	2.6327	1.22423
PerEarned	61	0.00	100.00	84.0034	31.91964

Table 44

Freshman class, portal login total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	89	0.00	4.00	2.7837	1.33596
PerEarned	89	0.00	100.00	80.7652	35.13221

Table 45

Freshman class, portal login total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	135	0.00	4.00	2.7346	1.11292
PerEarned	135	0.00	100.00	88.9945	25.42287

Table 46

Freshman class, D2L login total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	80	0.00	4.00	2.8088	1.24456
PerEarned	80	0.00	100.00	83.4226	32.50377

Table 47

Freshman class, D2L login total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	144	0.00	4.00	2.7238	1.18388
PerEarned	144	0.00	100.00	87.0038	28.32540

Table 48

Sophomore class, wireless total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	184	0.00	4.00	3.0266	1.05018
PerEarned	184	0.00	100.00	92.3279	22.12044

Table 49

Sophomore class, wireless total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	89	0.00	4.00	2.7176	1.12604
PerEarned	89	0.00	100.00	88.5929	26.71082

Table 50

Sophomore class, portal login total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	91	0.00	4.00	2.7914	1.28532
PerEarned	91	0.00	100.00	86.6040	30.75202

Table 51

Sophomore class, portal login total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	182	0.00	4.00	2.9931	0.96336
PerEarned	182	0.00	100.00	93.3634	18.99153

Table 52

Sophomore class, D2L login total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	90	0.00	4.00	2.8068	1.29409
PerEarned	90	0.00	100.00	86.1926	29.90017

Table 53

Sophomore class, D2L login total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	183	0.00	4.00	2.9844	0.96130
PerEarned	183	0.00	100.00	93.5288	19.66081

Table 54

Junior class, wireless total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	149	0.00	4.00	3.0354	1.11202
PerEarned	149	0.00	100.00	91.1858	24.31739

Table 55

Junior class, wireless total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	81	0.00	4.00	3.0978	0.90936
PerEarned	81	0.00	100.00	96.4359	14.33972

Table 56

Junior class, portal login total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	78	0.00	4.00	3.1577	1.08605
PerEarned	78	0.00	100.00	92.6129	23.82063

Table 57

Junior class, portal login total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	152	0.00	4.00	3.0059	1.02085
PerEarned	152	0.00	100.00	93.2512	20.21437

Table 58

Junior class, D2L login total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	76	0.00	4.00	3.1439	1.14981
PerEarned	76	0.00	100.00	91.6667	26.03412

Table 59

Junior class, D2L login total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	154	0.00	4.00	3.0146	0.98806
PerEarned	154	0.00	100.00	93.7099	18.85075

Table 60

Senior class, wireless total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	196	0.00	4.00	3.3084	0.99029
PerEarned	196	0.00	100.00	92.5596	22.98473

Table 61

Senior class, wireless total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	65	0.00	4.00	3.1217	0.97502
PerEarned	65	0.00	100.00	91.0658	22.55774

Table 62

Senior class, portal login total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	94	0.00	4.00	3.0381	1.23239
PerEarned	94	0.00	100.00	86.0994	31.08406

Table 63

Senior class, portal login total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	167	0.00	4.00	3.3879	0.79596
PerEarned	167	0.00	100.00	95.6145	15.59844

Table 64

Senior class, D2L login total < 17, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	85	0.00	4.00	3.1898	1.11352
PerEarned	85	0.00	100.00	89.3726	27.69107

Table 65

Senior class, D2L login total > 16, Summer 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	176	0.00	4.00	3.2967	0.92262
PerEarned	176	0.00	100.00	93.5471	20.04050

Fall 2019 Semester (15 weeks)

Table 66

All students, wireless total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	723	0.00	4.00	2.3789	1.35536
PerEarned	723	0.00	100.00	75.2117	37.33640

Table 67

All students, wireless total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	1772	0.00	4.00	2.7017	1.04095
PerEarned	1772	0.00	100.00	86.9328	24.76506

Table 68

All students, portal login total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	513	0.00	4.00	2.2768	1.37907
PerEarned	513	0.00	100.00	72.3272	39.13255

Table 69

All students, portal login total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	1982	0.00	4.00	2.6939	1.06672
PerEarned	1982	0.00	100.00	86.4375	25.59730

Table 70

All students, D2L login total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	632	0.00	4.00	2.3695	1.32034
PerEarned	632	0.00	100.00	76.1999	37.15896

Table 71

All students, D2L login total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	1863	0.00	4.00	2.6891	1.07471
PerEarned	1863	0.00	100.00	86.0250	25.87204

Table 72

Freshman class, wireless total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	263	0.00	4.00	1.7675	1.47104
PerEarned	263	0.00	100.00	56.9271	42.19336

Table 73

Freshman class, wireless total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	540	0.00	4.00	2.2055	1.19132
PerEarned	540	0.00	100.00	73.8305	32.30609

Table 74

Freshman class, portal login total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	162	0.00	4.00	1.4751	1.46569
PerEarned	162	0.00	100.00	46.2525	42.80529

Table 75

Freshman class, portal login total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	641	0.00	4.00	2.2104	1.21839
PerEarned	641	0.00	100.00	73.8649	32.73748

Table 76

Freshman class, D2L login total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	168	0.00	4.00	1.4126	1.45019
PerEarned	168	0.00	100.00	45.1210	42.90149

Table 77

Freshman class, D2L login total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	635	0.00	4.00	2.2339	1.20792
PerEarned	635	0.00	100.00	74.4252	32.21717

Table 78

Sophomore class, wireless total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	217	0.00	4.00	2.6384	1.18468
PerEarned	217	0.00	100.00	83.8394	31.87895

Table 79

Sophomore class, wireless total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	507	0.00	4.00	2.7959	0.92922
PerEarned	507	0.00	100.00	89.6120	20.23006

Table 80

Sophomore class, portal login total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	149	0.00	4.00	2.4218	1.22015
PerEarned	149	0.00	100.00	79.6436	34.25656

Table 81

Sophomore class, portal login total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	575	0.00	4.00	2.8334	0.93652
PerEarned	575	0.00	100.00	90.0166	20.67029

Table 82

Sophomore class, D2L login total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	203	0.00	4.00	2.4403	1.16673
PerEarned	203	0.00	100.00	81.0176	32.63264

Table 83

Sophomore class, D2L login total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	521	0.00	4.00	2.8689	0.92197
PerEarned	521	0.00	100.00	90.5564	19.77087

Table 84

Junior class, wireless total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	120	0.00	4.00	2.5395	1.12797
PerEarned	120	0.00	100.00	83.8098	30.16474

Table 85

Junior class, wireless total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	371	0.00	4.00	2.9200	0.86326
PerEarned	371	0.00	100.00	94.1531	16.79416

Table 86

Junior class, portal login total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	97	0.00	4.00	2.5472	1.13935
PerEarned	97	0.00	100.00	84.5999	30.26637

Table 87

Junior class, portal login total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	394	0.00	4.00	2.8959	0.88265
PerEarned	394	0.00	100.00	93.3548	18.07738

Table 88

Junior class, D2L login total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	125	0.00	4.00	2.7060	0.95834
PerEarned	125	0.00	100.00	90.6170	23.38008

Table 89

Junior class, D2L login total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	366	0.00	4.00	2.8683	0.94205
PerEarned	366	0.00	100.00	91.9695	20.56622

Table 90

Senior class, wireless total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	123	0.00	4.00	3.0718	1.03128
PerEarned	123	0.00	100.00	90.6985	23.91832

Table 91

Senior class, wireless total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	354	0.00	4.00	3.0948	0.80996
PerEarned	354	0.00	100.00	95.5149	14.12493

Table 92

Senior class, portal login total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	105	0.00	4.00	3.0580	1.00234
PerEarned	105	0.00	100.00	90.8370	23.76409

Table 93

Senior class, portal login total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	372	0.00	4.00	3.0976	0.83193
PerEarned	372	0.00	100.00	95.2428	14.86859

Table 94

Senior class, D2L login total < 31, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	136	0.00	4.00	3.1367	0.90639
PerEarned	136	0.00	100.00	94.1492	18.10213

Table 95

Senior class, D2L login total > 30, Fall 2019

	N	Minimum	Maximum	Mean	Std. Deviation
TermGPA	341	0.00	4.00	3.0698	0.85756
PerEarned	341	0.00	100.00	94.3223	16.98613

APPENDIX B

Regression Analysis Tables

Table 96

Logistic regression of all students, academic predictors only, Spring 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.562	0.132	18.044	1	.000	1.754
ColGPA	1.018	0.085	141.706	1	.000	2.767
HrsAtt	0.066	0.018	14.156	1	.000	1.069
Pell	-0.002	0.130	0.000	1	.986	0.998
Housing	0.067	0.157	0.180	1	.671	1.069
Race	-0.143	0.130	1.201	1	.273	0.867
SexCode	-0.128	0.133	0.932	1	.334	0.880
FGCode	-0.094	0.149	0.397	1	.528	0.910
Constant	-3.569	0.443	64.870	1	.000	0.028
Test			χ^2	*df*	*p*	
Likelihood ratio			297.448	8	.000	
Hosmer & Lameshow			19.827	8	.011	

Note. Negalkerke R^2 = .218. *c*-statistic = .770

Table 97

Logistic regression of all students, academic and technology predictors, Spring 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.663	0.139	22.600	1	.000	1.940
ColGPA	0.967	0.089	119.198	1	.000	2.630
HrsAtt	0.074	0.019	16.197	1	.000	1.077
Pell	-0.097	0.135	0.511	1	.475	0.908
Housing	-0.198	0.172	1.320	1	.251	0.821
Race	-0.146	0.136	1.163	1	.281	0.864
SexCode	-0.215	0.137	2.449	1	.118	0.807
FGCode	-0.167	0.154	1.173	1	.279	0.847
D2LPATT	0.102	0.013	58.375	1	.000	1.108
WirelessPATT	0.016	0.004	17.656	1	.000	1.016
Mobile	0.043	0.146	0.087	1	.768	1.044
Constant	-4.488	0.481	87.012	1	.000	0.011
Test			χ^2	*df*	*p*	
Likelihood ratio			402.458	11	.000	
Hosmer & Lameshow			2.966	8	.936	

Note. Negalkerke R^2 = .287. *c*-statistic = .804

Table 98

Logistic regression of Freshman, academic predictors only, Spring 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	1.095	0.178	37.718	1	.000	2.988
HrsAtt	-0.020	0.026	0.606	1	.436	0.980
Pell	0.058	0.181	0.104	1	.747	1.060
Housing	0.048	0.197	0.060	1	.807	1.049
Race	-0.236	0.178	1.755	1	.185	0.790
SexCode	-0.164	0.175	0.871	1	.351	0.849
FGCode	0.157	0.201	0.612	1	.434	1.170
Constant	-2.322	0.617	14.158	1	.000	0.098
Test			χ^2	*df*	*p*	
Likelihood ratio			50.478	7	.000	
Hosmer & Lameshow			22.702	8	.004	

Note. Negalkerke R^2 = .098. *c*-statistic = .659

Table 99

Logistic regression of Freshman, academic and technology predictors, Spring 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	1.373	0.200	47.308	1	.000	3.949
HrsAtt	-0.018	0.028	0.406	1	.524	0.982
Pell	-0.078	0.194	0.163	1	.687	0.925
Housing	-0.173	0.225	0.593	1	.441	0.841
Race	-0.236	0.192	1.519	1	.218	0.790
SexCode	-0.402	0.189	4.514	1	.034	0.669
FGCode	0.172	0.213	0.654	1	.419	1.188
D2LPATT	0.135	0.020	46.716	1	.000	1.145
WirelessPATT	0.011	0.005	4.275	1	.039	1.011
Mobile	0.344	0.205	2.799	1	.094	1.410
Constant	-3.860	0.710	29.569	1	.000	0.021
Test			χ^2	*df*	*p*	
Likelihood ratio			129.595	10	.000	
Hosmer & Lameshow			9.391	8	.310	

Note. Negalkerke R^2 = .238. *c*-statistic = .750

Table 100

Logistic regression of Sophomores, academic predictors only, Spring 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.076	0.254	0.090	1	.764	1.079
ColGPA	0.962	0.211	20.827	1	.000	2.617
HrsAtt	0.113	0.033	11.353	1	.001	1.119
Pell	0.127	0.246	0.268	1	.605	1.136
Housing	0.067	0.309	0.046	1	.829	1.069
Race	-0.027	0.246	0.012	1	.912	0.973
SexCode	0.410	0.239	2.942	1	.086	1.507
FGCode	-0.382	0.276	1.918	1	.166	0.682
Constant	-2.661	0.853	9.724	1	.002	0.070
Test			χ^2	*df*	*p*	
Likelihood ratio			57.585	8	.000	
Hosmer & Lameshow			8.760	8	.363	

Note. Negalkerke R^2 = .144. *c*-statistic = .737

Table 101

Logistic regression of Sophomores, academic and technology predictors, Spring 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.179	0.269	0.442	1	.506	1.196
ColGPA	0.792	0.221	12.900	1	.000	2.208
HrsAtt	0.133	0.035	14.653	1	.000	1.142
Pell	0.080	0.256	0.099	1	.753	1.084
Housing	-0.175	0.335	0.271	1	.602	0.840
Race	-0.005	0.258	0.000	1	.985	0.995
SexCode	0.371	0.249	2.220	1	.136	1.449
FGCode	-0.462	0.288	2.575	1	.109	0.630
D2LPATT	0.098	0.025	16.003	1	.000	1.103
WirelessPATT	0.024	0.008	9.919	1	.002	1.024
Mobile	-0.540	0.263	4.222	1	.040	0.583
Constant	-3.329	0.915	13.236	1	.000	0.036
Test			χ^2	*df*	*p*	
Likelihood ratio			94.262	11	.000	
Hosmer & Lameshow			5.551	8	.697	

Note. Negalkerke R^2 = .229. *c*-statistic = .793

Table 102

Logistic regression of Juniors, academic predictors only, Spring 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.677	0.371	3.328	1	.068	1.967
ColGPA	0.857	0.387	4.912	1	.027	2.356
HrsAtt	0.046	0.043	1.153	1	.283	1.047
Pell	0.320	0.338	0.897	1	.344	1.377
Housing	0.941	0.533	3.115	1	.078	2.564
Race	-0.813	0.332	5.994	1	.014	0.443
SexCode	-0.318	0.341	0.869	1	.351	0.728
FGCode	-0.211	0.388	0.297	1	.586	0.809
Constant	-2.843	1.240	5.255	1	.022	0.058
Test			χ^2	*df*	*p*	
Likelihood ratio			37.136	8	.000	
Hosmer & Lameshow			7.547	8	.479	

Note. Negalkerke R^2 = .162. *c*-statistic = .738

Table 103

Logistic regression of Juniors, academic and technology predictors, Spring 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.814	0.391	4.340	1	.037	2.256
ColGPA	0.619	0.394	2.474	1	.116	1.857
HrsAtt	0.057	0.045	1.608	1	.205	1.059
Pell	0.274	0.350	0.609	1	.435	1.315
Housing	0.654	0.592	1.219	1	.270	1.924
Race	-0.965	0.346	7.788	1	.005	0.381
SexCode	-0.550	0.359	2.341	1	.126	0.577
FGCode	-0.341	0.404	0.713	1	.398	0.711
D2LPATT	0.096	0.034	8.111	1	.004	1.100
WirelessPATT	0.016	0.011	2.138	1	.144	1.016
Mobile	0.352	0.414	0.724	1	.395	1.422
Constant	-3.345	1.283	6.801	1	.009	0.035
Test			χ^2	*df*	*p*	
Likelihood ratio			54.795	11	.000	
Hosmer & Lameshow			19.478	8	.013	

Note. Negalkerke R^2 = .234. *c*-statistic = .781

Table 104

Logistic regression of Seniors, academic predictors only, Spring 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.225	0.520	0.186	1	.666	1.252
ColGPA	3.134	0.680	21.218	1	.000	22.976
HrsAtt	0.214	0.064	11.319	1	.001	1.239
Pell	-0.476	0.510	0.871	1	.351	0.621
Housing	-0.986	0.739	1.778	1	.182	0.373
Race	0.278	0.551	0.254	1	.614	1.320
SexCode	0.039	0.510	0.006	1	.939	1.040
FGCode	-0.877	0.565	2.408	1	.121	0.416
Constant	-9.160	2.145	18.238	1	.000	0.000
Test			χ^2	*df*	*p*	
Likelihood ratio			54.364	8	.000	
Hosmer & Lameshow			3.311	8	.913	

Note. Negalkerke R^2 = .368. *c*-statistic = .882

Table 105

Logistic regression of Seniors, academic and technology predictors, Spring 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.297	0.537	0.306	1	.580	1.346
ColGPA	3.140	0.710	19.528	1	.000	23.097
HrsAtt	0.210	0.068	9.478	1	.002	1.234
Pell	-0.718	0.544	1.741	1	.187	0.488
Housing	-1.411	0.796	3.146	1	.076	0.244
Race	0.254	0.558	0.207	1	.649	1.289
SexCode	0.199	0.532	0.139	1	.709	1.220
FGCode	-1.049	0.622	2.843	1	.092	0.350
D2LPATT	0.038	0.044	0.734	1	.392	1.039
WirelessPATT	0.021	0.016	1.599	1	.206	1.021
Mobile	0.340	0.697	0.237	1	.626	1.405
Constant	-9.888	2.281	18.787	1	.000	0.000
Test			χ^2	*df*	*p*	
Likelihood ratio			58.149	11	.000	
Hosmer & Lameshow			10.579	8	.227	

Note. Negalkerke R^2 = .392. *c*-statistic = .894

Summer 2019 Semester

Table 106

Logistic regression of all students, academic predictors only, Summer 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.253	0.225	1.271	1	.259	1.288
ColGPA	0.585	0.144	16.457	1	.000	1.796
HrsAtt	0.003	0.039	0.005	1	.945	1.003
Pell	-0.139	0.229	0.369	1	.543	0.870
Housing	-0.177	0.367	0.232	1	.630	0.838
Race	-0.199	0.227	0.772	1	.380	0.820
SexCode	0.056	0.237	0.056	1	.813	1.058
FGCode	-0.102	0.265	0.149	1	.699	0.903
Constant	-0.359	0.713	0.254	1	.614	0.698
Test			χ^2	*df*	*p*	
Likelihood ratio			30.535	8	.000	
Hosmer & Lameshow			6.564	8	.584	

Note. Negalkerke R^2 = .069. *c*-statistic = .667

Table 107

Logistic regression of all students, academic and technology predictors, Summer 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.360	0.235	2.339	1	.126	1.433
ColGPA	0.540	0.149	13.206	1	.000	1.716
HrsAtt	0.013	0.039	0.118	1	.731	1.014
Pell	-0.222	0.234	0.904	1	.342	0.801
Housing	-0.405	0.405	0.998	1	.318	0.667
Race	-0.145	0.232	0.390	1	.533	0.865
SexCode	0.020	0.243	0.007	1	.935	1.020
FGCode	-0.149	0.269	0.308	1	.579	0.862
D2LPATT	0.047	0.017	7.630	1	.006	1.048
WirelessPATT	0.022	0.013	2.797	1	.094	1.023
Mobile	0.036	0.234	0.024	1	.878	1.037
Constant	-1.016	0.755	1.809	1	.179	0.362
Test			χ^2	*df*	*p*	
Likelihood ratio			44.352	11	.000	
Hosmer & Lameshow			14.585	8	.068	

Note. Negalkerke R^2 = .099. *c*-statistic = .710

Table 108

Logistic regression of all Freshman, academic predictors only, Summer 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.416	0.348	1.424	1	.233	1.515
HrsAtt	-0.084	0.090	0.858	1	.354	0.920
Pell	0.130	0.421	0.095	1	.758	1.138
Housing	-0.197	0.584	0.114	1	.736	0.821
Race	-0.436	0.376	1.342	1	.247	0.647
SexCode	-0.333	0.409	0.660	1	.417	0.717
FGCode	0.482	0.470	1.054	1	.305	1.620
Constant	1.000	1.199	0.696	1	.404	2.719
Test			χ^2	*df*	*p*	
Likelihood ratio			5.265	7	.628	
Hosmer & Lameshow			5.583	8	.694	

Note. Negalkerke R^2 = .041. *c*-statistic = .622

Table 109

Logistic regression of Freshman, academic and technology predictors, Summer 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.572	0.369	2.410	1	.121	1.772
HrsAtt	-0.073	0.093	0.614	1	.433	0.930
Pell	-0.043	0.443	0.009	1	.924	0.958
Housing	-0.163	0.650	0.063	1	.802	0.850
Race	-0.408	0.388	1.105	1	.293	0.665
SexCode	-0.398	0.441	0.814	1	.367	0.672
FGCode	0.425	0.482	0.778	1	.378	1.530
D2LPATT	0.061	0.028	4.807	1	.028	1.063
WirelessPATT	0.010	0.018	0.296	1	.586	1.010
Mobile	-0.084	0.413	0.041	1	.839	0.919
Constant	0.097	1.257	0.006	1	.939	1.101
Test			χ^2	*df*	*p*	
Likelihood ratio			12.123	10	.277	
Hosmer & Lameshow			5.210	8	.735	

Note. Negalkerke R^2 = .092. *c*-statistic = .704

Table 110

Logistic regression of Sophomores, academic predictors only, Summer 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.737	0.419	3.086	1	.079	2.089
ColGPA	0.908	0.373	5.924	1	.015	2.480
HrsAtt	0.070	0.073	0.912	1	.340	1.072
Pell	0.060	0.427	0.019	1	.889	1.061
Housing	-0.640	0.600	1.136	1	.287	0.528
Race	0.160	0.434	0.136	1	.712	1.174
SexCode	-0.167	0.440	0.144	1	.705	0.846
FGCode	0.431	0.539	0.639	1	.424	1.539
Constant	-3.242	1.505	4.643	1	.031	0.039
Test			χ^2	*df*	*p*	
Likelihood ratio			16.617	8	.034	
Hosmer & Lameshow			8.055	8	.428	

Note. Negalkerke R^2 = .121. *c*-statistic = .708

Table 111

Logistic regression of Sophomores, academic and technology predictors, Summer 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.844	0.444	3.607	1	.058	2.325
ColGPA	0.825	0.386	4.566	1	.033	2.281
HrsAtt	0.065	0.074	0.769	1	.381	1.067
Pell	0.063	0.433	0.021	1	.884	1.065
Housing	-0.637	0.647	0.971	1	.324	0.529
Race	0.211	0.440	0.230	1	.632	1.235
SexCode	-0.194	0.442	0.194	1	.660	0.823
FGCode	0.435	0.550	0.626	1	.429	1.544
D2LPATT	0.018	0.026	0.506	1	.477	1.018
WirelessPATT	-0.011	0.020	0.285	1	.593	0.990
Mobile	0.268	0.450	0.353	1	.552	1.307
Constant	-3.509	1.543	5.171	1	.023	0.030
Test			χ^2	*df*	*p*	
Likelihood ratio			17.861	11	.085	
Hosmer & Lameshow			4.995	8	.758	

Note. Negalkerke R^2 = .130. *c*-statistic = .714

Table 112

Logistic regression of Juniors, academic predictors only, Summer 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	-0.140	0.562	0.062	1	.804	0.870
ColGPA	0.655	0.502	1.701	1	.192	1.925
HrsAtt	-0.100	0.080	1.538	1	.215	0.905
Pell	0.345	0.526	0.430	1	.512	1.412
Housing	-0.369	1.128	0.107	1	.744	0.691
Race	-0.647	0.508	1.620	1	.203	0.524
SexCode	0.703	0.524	1.800	1	.180	2.020
FGCode	-0.510	0.584	0.764	1	.382	0.600
Constant	1.063	1.866	0.324	1	.569	2.894
Test			χ^2	*df*	*p*	
Likelihood ratio			9.383	8	.311	
Hosmer & Lameshow			6.409	8	.602	

Note. Negalkerke R^2 = .093. *c*-statistic = .700

Table 113

Logistic regression of Juniors, academic and technology predictors, Summer 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	-0.104	0.594	0.031	1	.861	0.901
ColGPA	0.598	0.524	1.303	1	.254	1.818
HrsAtt	-0.107	0.084	1.617	1	.203	0.898
Pell	0.228	0.539	0.179	1	.672	1.256
Housing	-2.326	1.367	2.896	1	.089	0.098
Race	-0.658	0.533	1.521	1	.217	0.518
SexCode	0.986	0.578	2.908	1	.088	2.679
FGCode	-0.400	0.607	0.434	1	.510	0.671
D2LPATT	0.030	0.036	0.681	1	.409	1.031
WirelessPATT	0.091	0.047	3.832	1	.050	1.095
Mobile	-0.169	0.547	0.096	1	.757	0.844
Constant	0.539	1.971	0.075	1	.785	1.714
Test			χ^2	*df*	*p*	
Likelihood ratio			16.987	11	.108	
Hosmer & Lameshow			11.123	8	.195	

Note. Negalkerke R^2 = .166. *c*-statistic = .768

Table 114

Logistic regression of Seniors, academic predictors only, Summer 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	-0.403	0.533	0.572	1	.449	0.668
ColGPA	1.818	0.629	8.346	1	.004	6.158
HrsAtt	0.007	0.081	0.008	1	.930	1.007
Pell	-0.647	0.537	1.451	1	.228	0.524
Housing	0.044	1.209	0.001	1	.971	1.045
Race	0.303	0.574	0.279	1	.597	1.354
SexCode	-0.144	0.575	0.063	1	.802	0.866
FGCode	-0.455	0.645	0.497	1	.481	0.635
Constant	-1.641	2.094	0.615	1	.433	0.194
Test			χ^2	*df*	*p*	
Likelihood ratio			12.530	8	.129	
Hosmer & Lameshow			13.663	8	.091	

Note. Negalkerke R^2 = .135. *c*-statistic = .754

Table 115

Logistic regression of Seniors, academic and technology predictors, Summer 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.150	0.618	0.059	1	.809	1.161
ColGPA	1.844	0.685	7.243	1	.007	6.320
HrsAtt	0.052	0.087	0.366	1	.545	1.054
Pell	-1.120	0.594	3.552	1	.059	0.326
Housing	-1.066	1.372	0.604	1	.437	0.344
Race	0.517	0.637	0.657	1	.418	1.676
SexCode	0.165	0.609	0.074	1	.786	1.180
FGCode	-0.677	0.722	0.879	1	.348	0.508
D2LPATT	0.225	0.084	7.263	1	.007	1.253
WirelessPATT	0.161	0.095	2.867	1	.090	1.175
Mobile	-0.361	0.634	0.324	1	.569	0.697
Constant	-5.055	2.600	3.781	1	.052	0.006
Test			χ^2	*df*	*p*	
Likelihood ratio			27.406	11	.004	
Hosmer & Lameshow			5.337	8	.721	

Note. Negalkerke R^2 = .283. *c*-statistic = .830

Fall 2019 Semester

Table 116

Logistic regression of all students, academic predictors only, Fall 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.435	0.140	9.717	1	.002	1.545
ColGPA	0.901	0.085	112.918	1	.000	2.461
HrsAtt	0.046	0.020	5.425	1	.020	1.047
Pell	-0.107	0.143	0.562	1	.453	0.898
Housing	0.079	0.191	0.173	1	.678	1.083
Race	-0.067	0.145	0.216	1	.642	0.935
SexCode	0.159	0.141	1.270	1	.260	1.172
FGCode	0.130	0.167	0.601	1	.438	1.138
Constant	-2.623	0.458	32.869	1	.000	0.073
Test			χ^2	*df*	*p*	
Likelihood ratio			192.026	8	.000	
Hosmer & Lameshow			3.956	8	.861	

Note. Negalkerke R^2 = .165. *c*-statistic = .741

Table 117

Logistic regression of all students, academic and technology predictors, Fall 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.486	0.150	10.551	1	.001	1.626
ColGPA	0.814	0.091	80.575	1	.000	2.256
HrsAtt	0.067	0.022	9.660	1	.002	1.070
Pell	-0.133	0.151	0.773	1	.379	0.876
Housing	-0.498	0.216	5.297	1	.021	0.608
Race	-0.149	0.153	0.947	1	.331	0.862
SexCode	0.117	0.149	0.623	1	.430	1.124
FGCode	0.059	0.175	0.114	1	.735	1.061
Mobile	-0.391	0.154	6.407	1	.011	0.676
D2LPATT	0.079	0.012	43.358	1	.000	1.082
WirelessPATT	0.038	0.005	50.478	1	.000	1.039
Constant	-3.557	0.506	49.504	1	.000	0.029
Test			χ^2	*df*	*p*	
Likelihood ratio			330.948	11	.000	
Hosmer & Lameshow			19.397	8	.013	

Note. Negalkerke R^2 = .275. *c*-statistic = .810

Table 118

Logistic regression of all Freshman, academic predictors only, Fall 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.938	0.167	31.435	1	.000	2.554
HrsAtt	0.026	0.026	1.060	1	.303	1.027
Pell	-0.027	0.167	0.027	1	.870	0.973
Housing	0.107	0.191	0.314	1	.575	1.113
Race	-0.335	0.167	4.015	1	.045	0.715
SexCode	0.199	0.168	1.411	1	.235	1.221
FGCode	0.140	0.186	0.560	1	.454	1.150
Constant	-2.534	0.540	22.040	1	.000	0.079
Test			χ^2	*df*	*p*	
Likelihood ratio			49.074	7	.000	
Hosmer & Lameshow			10.280	8	.246	

Note. Negalkerke R^2 = .087. *c*-statistic = .657

Table 119

Logistic regression of Freshman, academic and technology predictors, Fall 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	1.104	0.191	33.547	1	.000	3.015
HrsAtt	0.030	0.031	0.957	1	.328	1.030
Pell	-0.117	0.183	0.410	1	.522	0.890
Housing	-0.318	0.229	1.927	1	.165	0.728
Race	-0.438	0.185	5.604	1	.018	0.645
SexCode	0.030	0.183	0.027	1	.869	1.031
FGCode	-0.011	0.204	0.003	1	.959	0.990
Mobile	0.003	0.229	0.000	1	.989	1.003
D2LPATT	0.108	0.015	51.975	1	.000	1.114
WirelessPATT	0.028	0.006	25.353	1	.000	1.028
Constant	-4.030	0.639	39.781	1	.000	0.018
Test			χ^2	*df*	*p*	
Likelihood ratio			174.625	10	.000	
Hosmer & Lameshow			9.305	8	.317	

Note. Negalkerke R^2 = .284. *c*-statistic = .776

Table 120

Logistic regression of Sophomores, academic predictors only, Fall 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.392	0.261	2.257	1	.133	1.480
ColGPA	0.892	0.214	17.383	1	.000	2.441
HrsAtt	0.031	0.038	0.635	1	.426	1.031
Pell	0.038	0.255	0.022	1	.882	1.039
Housing	0.002	0.317	0.000	1	.995	1.002
Race	-0.103	0.255	0.164	1	.685	0.902
SexCode	0.539	0.239	5.092	1	.024	1.714
FGCode	0.227	0.321	0.503	1	.478	1.255
Constant	-2.469	0.862	8.209	1	.004	0.085
Test			χ^2	*df*	*p*	
Likelihood ratio			41.291	8	.000	
Hosmer & Lameshow			10.196	8	.252	

Note. Negalkerke R^2 = .109. *c*-statistic = .713

Table 121

Logistic regression of Sophomores, academic and technology predictors, Fall 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.520	0.275	3.578	1	.059	1.682
ColGPA	0.770	0.223	11.952	1	.001	2.159
HrsAtt	0.055	0.040	1.846	1	.174	1.057
Pell	-0.068	0.263	0.066	1	.797	0.935
Housing	-0.360	0.362	0.988	1	.320	0.698
Race	-0.201	0.266	0.575	1	.448	0.818
SexCode	0.542	0.247	4.824	1	.028	1.720
FGCode	0.271	0.330	0.675	1	.411	1.311
Mobile	-0.134	0.266	0.254	1	.614	0.875
D2LPATT	0.084	0.023	13.796	1	.000	1.087
WirelessPATT	0.017	0.008	4.490	1	.034	1.017
Constant	-3.425	0.925	13.702	1	.000	0.033
Test			χ^2	*df*	*p*	
Likelihood ratio			68.785	11	.000	
Hosmer & Lameshow			10.857	8	.210	

Note. Negalkerke R^2 = .177. *c*-statistic = .760

Table 122

Logistic regression of Juniors, academic predictors only, Fall 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.045	0.392	0.013	1	.908	1.046
ColGPA	1.264	0.388	10.586	1	.001	3.539
HrsAtt	0.059	0.048	1.511	1	.219	1.061
Pell	-0.503	0.352	2.044	1	.153	0.605
Housing	-0.200	0.510	0.154	1	.695	0.819
Race	0.158	0.370	0.181	1	.670	1.171
SexCode	0.053	0.370	0.020	1	.887	1.054
FGCode	-0.235	0.391	0.362	1	.547	0.790
Constant	-1.952	1.303	2.244	1	.134	0.142
Test			χ^2	*df*	*p*	
Likelihood ratio			21.504	8	.006	
Hosmer & Lameshow			8.643	8	.373	

Note. Negalkerke R^2 = .101. *c*-statistic = .719

Table 123

Logistic regression of Juniors, academic and technology predictors, Fall 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.120	0.408	0.087	1	.768	1.128
ColGPA	1.135	0.411	7.617	1	.006	3.112
HrsAtt	0.061	0.051	1.427	1	.232	1.063
Pell	-0.496	0.362	1.872	1	.171	0.609
Housing	-0.923	0.554	2.770	1	.096	0.397
Race	0.099	0.385	0.066	1	.797	1.104
SexCode	-0.008	0.388	0.000	1	.984	0.992
FGCode	-0.156	0.409	0.146	1	.702	0.855
Mobile	-0.053	0.394	0.018	1	.892	0.948
D2LPATT	0.034	0.024	1.961	1	.161	1.035
WirelessPATT	0.042	0.013	10.223	1	.001	1.043
Constant	-2.623	1.397	3.524	1	.060	0.073
Test			χ^2	*df*	*p*	
Likelihood ratio			39.435	11	.000	
Hosmer & Lameshow			7.195	8	.516	

Note. Negalkerke R^2 = .182. *c*-statistic = .786

Table 124

Logistic regression of Seniors, academic predictors only, Fall 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	1.060	0.636	2.776	1	.096	2.886
ColGPA	1.126	0.731	2.370	1	.124	3.082
HrsAtt	0.060	0.075	0.644	1	.422	1.062
Pell	0.862	0.702	1.506	1	.220	2.368
Housing	0.377	1.122	0.113	1	.737	1.458
Race	-0.437	0.619	0.498	1	.480	0.646
SexCode	-0.236	0.641	0.135	1	.713	0.790
FGCode	0.243	0.802	0.092	1	.762	1.275
Constant	-3.923	2.346	2.796	1	.095	0.020
Test			χ^2	*df*	*p*	
Likelihood ratio			13.016	8	.111	
Hosmer & Lameshow			14.217	8	.076	

Note. Negalkerke R^2 = .132. *c*-statistic = .793

Table 125

Logistic regression of Seniors, academic and technology predictors, Fall 2019

Predictor	β	SE β	Wald's χ^2	*df*	*p*	*e*β (odds ratio)
HSGPA	0.868	0.627	1.917	1	.166	2.382
ColGPA	1.293	0.744	3.015	1	.083	3.642
HrsAtt	0.072	0.085	0.717	1	.397	1.075
Pell	0.972	0.750	1.683	1	.194	2.644
Housing	-0.495	1.243	0.159	1	.690	0.609
Race	-0.330	0.647	0.260	1	.610	0.719
SexCode	-0.223	0.673	0.110	1	.741	0.800
FGCode	0.251	0.829	0.091	1	.762	1.285
Mobile	-1.049	0.641	2.675	1	.102	0.350
D2LPATT	0.058	0.047	1.531	1	.216	1.060
WirelessPATT	0.057	0.029	3.911	1	.048	1.058
Constant	-4.749	2.534	3.513	1	.061	0.009
Test			χ^2	*df*	*p*	
Likelihood ratio			21.677	11	.027	
Hosmer & Lameshow			7.138	8	.522	

Note. Negalkerke R^2 = .218. *c*-statistic = .840

APPENDIX C

IRB Protocol Exemption Reports

Institutional Review Board (IRB)
For the Protection of Human Research Participants

PROTOCOL EXEMPTION REPORT

Protocol Number:	03929-2019	**Responsible Researcher:**	Alan Ours
Supervising Faculty:	Dr. W. Todd Watson		
Project Title:	*Assessment of Technology Use Data Contribution to Early Alert Efforts at an Access Based Institution.*		

INSTITUTIONAL REVIEW BOARD DETERMINATION:

This research protocol is **Exempt** from Institutional Review Board (IRB) oversight under Exemption **Category 4**. Your research study may begin immediately. If the nature of the research project changes such that exemption criteria may no longer apply, please consult with the IRB Administrator (irb@valdosta.edu) before continuing your research.

ADDITIONAL COMMENTS:

- *Upon completion of this research study all data (data list, email correspondence, etc.) must be securely maintained (locked file cabinet, password protected computer, etc.) and accessible only by the researcher for a minimum of 3 years.*

☒ ***If this box is checked, please submit any documents you revise to the IRB Administrator at irb@valdosta.edu to ensure an updated record of your exemption.***

Elizabeth Ann Olphie 09.26.2019

Elizabeth Ann Olphie, IRB Administrator

Thank you for submitting an IRB application.

Please direct questions to irb@valdosta.edu or 229-253-2947.

Revised: 06.02.16

Institutional Review Board
October 9, 2019

Alan Ours
Chief Information Officer
Department of Technology Services

As Chair of the College of Coastal Georgia IRB, I have reviewed the application **IRB #2020-05** for an investigation entitled *"Assessment of Technology Use Data Contribution to Early Alert Efforts in Higher Education"*. This investigation falls within the category defined by U.S. Department of Health and Human Services in 45 CFR 46.104 (d)(4)(ii) as appropriate for **exemption**.

The IRB grants approval of this application for the period of one year in accordance with 45 CFR 46.111, 45 CFR 46.116 (a), and waiver of informed consent in accordance with 45 CFR 46.117. Please note however, any substantive changes to this proposal may alter its status and must be resubmitted for review prior to implementation of any changes in protocol.

The IRB will review the status of this investigation on**10/09/2020**. Please submit the Request for Extension-Revision-Completion-Annual Review form on the College website (**https://www.ccga.edu/IRB**) prior to that date.

We appreciate the opportunity to review the proposed research and look forward to your continued participation with the board. Please contact me if you have questions regarding this response.

Sincerely,

Dr. Aurora Ramos Nuñez, PhD, Chair IRG
Dr. Lauren Boardman, PhD, Vice Chair IRB
Cc: Connie Hiott, Administrator IRB