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THE USE OF DINING DATA TO INCREASE RETENTION AND

ACADEMIC SUCCESS IN RESIDENTIAL FIRST-YEAR STUDENTS

A Dissertation

Presented to

The Faculty of the University of Lynchburg

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Education (Ed.D.)

by

Hailey Manicone, B.S., M.Ed.

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April 2022

APPROVAL OF DISSERTATION

University of Lynchburg
Lynchburg, Virginia

Student Name: Hailey Anne Manicone Date: April 7, 2022

Dissertation Topic: The Use of Dining Data to Increase Retention and Academic Success in Residential First-Year Students

APPROVAL OF THE DISSERTATION

This dissertation, The Use of Dining Data to Increase Retention and Academic Success in Residential First-Year Students, has been approved by the EdD Faculty of the University of Lynchburg in partial fulfillment of the requirements for the EdD degree.

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Roger E. Jones, Dean of Graduate Studies Date: April 12, 2022

Filed in the Office of
Graduate Studies

DEDICATION

When I was a little girl, I never dreamed of writing a dissertation that contributed to the field of higher education research, however, my friends and family supported me along the way as the Lord orchestrated my steps. This dissertation is dedicated to them and to the future students who preserve and complete their degrees with the support of proactive and engaged institutions.

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List of Abbreviations

Academic Analytics (AA)

Age of Onset (AOO)

Association to Advance Collegiate Schools of Business (AACS)

Center for Disease Control (CDC)

Community College Survey of Student Engagement (CCSSE)

Education Data Mining (EDM)

Free Application for Federal Student Aid (FAFSA)

Grade Point Average (GPA)

Learning Analytics (LA)

Major Depression Disorder (MDD)

National Collegiate Athletic Association (NCAA)

National Survey of Student Engagement (NSSE)

Science, Technology, Engineering, and Mathematics (STEM)

Self-Description Questionnaire III (SDQ III)

Standard Deviation (SD)

ABSTRACT

Higher education leaders have been conducting research over the last 50 years to pinpoint why students enroll in college and then end up leaving. Research shows that there is not a single factor that influences a student's decision, but it is a variety of factors. Influential factors include class attendance, a sense of belonging, motivation, academic rigor and performance, finances, and more. A student's physical wellness and mental state can also impact their academic success and life while in college. First-year students often experience depression, anxiety, and loneliness as they try to successfully transition to college. Most of these influential factors are quantified and measured by institutions in real-time through predictive analytics to identify students at risk of leaving. One data point that has not been thoroughly researched is dining data. This non-experimental, causal-comparison study investigated the relationship between dining data and academic success and retention. Analysis of the data showed that dining data can predict academic success and retention, however, the strongest correlation existed between a significant change in dining habits predicting persistence into the next semester. The findings indicate that dining data should be collected by institutions and integrated into predictive analytics to identify at-risk students. Further research should be conducted to generalize the use of dining data in predictive analytics as well as investigate how dining data can be paired with other data points to further identify students in need of assistance.

Keywords: retention, student persistence, academic success, dining data, predictive analytics, big data, physical wellness, mental health

CHAPTER ONE

INTRODUCTION

Overview

For years, higher education institutions have been working diligently to lower student dropout rates, in order to increase retention and graduation rates. This chapter introduces factors that contribute to retention and academic success and describes the importance of mental health and physical wellness in first-year students. The chapter also includes a problem statement that gave direction to this causal-correlational study. The study investigated the relationship between dining interactions and retention and academic success.

Background

Institutions seek to understand why a student stays at or leaves an institution. With the technological advancements of the last twenty years, institutions have prioritized the use of data in their retention efforts. If a student leaves an institution, it is most likely after their first year and before their second year (De Clercq et al., 2018). It is clear, however, that students leave or stay at an institution for various reasons, such as sense of belonging, satisfaction with degree program, stress levels, and more (Boyd et al., 2020; Sokratous et al., 2013; van Rooij et al., 2018). Institutions have policies, programs, and initiatives that aim to promote success for first year students. These initiatives include first-year seminars and orientations (Al-Sheeb et al., 2018; Culver & Bowman, 2020).

Physical wellness and good mental health in college students, and especially in first-year students, is essential (Upcraft & Gardner, 1989). Adjusting to college life, academic rigor, and social freedom is complex. It can result in high-stress levels, depression, and a change in eating habits (Goldstein et al., 2015; Hsu & Chiang, 2020). These can drastically impact students' brain functioning and thus influence their academic success (Ferreira-Pego et al., 2020).

While there are various tools institutions can use to assess the wellness of their students, most tools require the students to volunteer information. Not all students are willing to participate or disclose good and bad habits when asked. The literature did not reveal a way in which institutions can gather information about student wellness without asking them.

Problem Statement

With the advancements in data analysis in higher education, institutions use data analytics to evaluate current programs and processes to increase student success and retention (Picciano, 2012). To mitigate the dropout problem after the first year, institutions have initiatives that provide support and an opportunity for early connections (Al-Sheeb et al., 2018). Current research indicates that various data points, like GPA and class attendance, inform decisions (De Clerq et al., 2018; Saunders-Scott et al., 2018). These data points are not always available in real or near real time and may not be reliable. Institutions are looking for new ways to use data to personalize their services and student interactions to increase student retention.

Purpose Statement

The purpose of this causal-correlational study was to see whether dining data in the form of weekly interactions can predict retention and academic success. If so, dining data may be used as a theoretical proxy for physical wellness and mental health. Dining data is collected in real or near-real time. While the dining interactions themselves may not fully contribute to retention and academic success, the frequency of the interactions may be evidence of the student’s physical and mental wellness, which is important to student success. As such, the relationship between the average weekly dining interactions and first-year retention and academic success were investigated. A significant change in a student's dining habits could result from stress, different social interactions, traumatic life events, and more since research indicates these experiences impact eating habits.

Significance of the Study

This study may help generalize the concept of using dining data in predictive analytics as a proxy for physical wellness and mental health. Since the results of the statistical tests were significant and all null hypotheses were rejected, institutions may serve students more effectively by integrating dining data into their current data analysis. The most significant finding of this study was the connection between changes in dining habits and whether a student persisted into the next semester. This study may also contribute to current literature about what data is used in predictive analytics.

Research Questions

In order to explore the relationship between dining data in the form of weekly interactions and academic success and retention in first-year students, the research questions below guided the study.

RQ1: What is the relationship between a student’s weekly average dining interactions Monday through Friday and their academic success during their first and second semesters at a large private university?

RQ2: What is the relationship between a student’s weekly average dining interactions Monday through Friday and their persistence into their second and third semesters at a large private university?

RQ3: What is the effect of a significant change in dining habits on a student’s academic success during their first and second semesters at a large private university?

RQ4: What is the effect of a significant change in dining habits on a student's persistence into their second and third semesters at a large private university?

Null Hypothesis

$N_0$1: A student's weekly average dining interactions Monday through Friday has no relationship to their academic success during their first and second semester at a large private university.

$N_0$2: A student's weekly average dining interactions Monday through Friday has no relationship to their persistence into their second and third semester at a large private university.

$N_0$3: A significant change in dining habits does not affect a student's academic success during their first and second semester at a large private university.

$N_0$4: A significant change in dining habits does not affect a student's persistence into their second and third semester at a large private university.

Definitions of Key Terms

To ensure the study is fully understood, please refer to the definitions of key terms below.

1. Academic success - When students achieve their academic goals, thrive in all their spaces, and complete the required course work for their degree completion
2. Data – a unit of information
3. Dining data – Data collected based on interactions students have with dining services
4. Matriculation – When students attend their first class at the institution, solidifying their enrollment at the institution.
5. Persistence – A student's journey towards degree completion (Bahi et al., 2015).
6. Pre-matriculation – The stage a student is in before they attend their first class at an institution.

7. Retention – The rate at which a student enrolls in the next term or completed their degree program at an institution (Schuh, 2017).
8. Well-being – According to the Center for Disease Control (CDC), while there is no true definition of well-being, it can be explained as a state of being in which an individual is satisfied with all aspects of life (CDC, 2018).
9. Wellness – The National Wellness Institution, wellness is “an active process through which people become aware of, and make choices toward, a more successful existence” (2021).

CHAPTER TWO

LITERATURE REVIEW

Overview

Students choose various paths after high school, with a common path taking students to a two or four-year college or university. Students enter higher education intending to complete a two or four-year degree and seek employment. However, a little over half of the nation's college students finish their degree within six years of starting (Astin, 1984; Sparkman et al., 2012). Over the last 50 years, institutions have sought to develop and implement strategies to help students succeed. Student success in college leads to higher graduation rates and retention rates, but no one strategy leads to student success (Purdie & Rosser, 2011).

Retention, one of the most used metrics of success for an institution, reflects the rate at which a student stays at the institution and is thus persisting towards degree completion. Retention is a foundational concept institutions prioritize. Research shows that no one single factor influences student success and retention. Every interaction a student has, in or outside the institution, impacts their decision to continue their education (Picton, 2018).

Students want to be cared for, stay in school, and reach their goals. As one student explained, "[w]e, your children, are faced with a tremendous difficulty in terms of completion of our studies and consequently obtaining our qualifications. We are frustrated, vulnerable, emotional, and injured – please intervene…" (Badat, 2016, p. 84). While this student asked for help, not all do. Institutions must find ways to meet the students where they are and help them persist towards degree completion. Institutions can no longer wait for the students to ask for help. Using data to inform decisions that increases retention may do just that.

Retention Frameworks

Since researchers and institutions have been investigating the college experience for over 50 years, various theories and frameworks have been developed. These theories address different facets of the student experience in higher education, like campus climate, identity structures, academic success and retention. This section will describe, as well as compare student success and retention theories that are most pertinent to this study.

Vincent Tinto is one of the most well-known higher education researchers whose framework provides the foundation for retention research. Tinto's 1975 framework concluded that students stay in college because of an ongoing process of successful social integration (Tinto, 1975). This successful integration is not from the institution's perspective but that of the student (Bauman et al., 2019). Students must believe that they are integrating into their community and college life successfully in order to move forward with confidence. Tinto has reviewed, edited, and added to his 1975 theory to incorporate the importance of motivation, academic skills, and student involvement (Picton et al., 2018; Tinto, 1993, 2007).

Another foundational framework is that of Alexander Astin. His theory of involvement was published in 1993 and indicated the importance of a student's inputs, environments, and outcomes. This means that institutions should view students as holistic people who are the embodiment of what they have experienced, what is around them, and how those two aspects influence what they do. He boasted that his framework was easy to follow and was encompassing of all aspects of students. His framework set the tone for how institutions view their students as complex individuals influenced by who they are, what is around them, and what they do (Astin, 1993, 1999).

David McMillan and David Chavis also created a critical framework used in retention efforts in higher education. They developed a conceptual and empirical framework about community. The framework includes four factors: membership, influence, fulfillment of needs, and shared emotional connection (McMillan & Chavis, 1986). This means that students are impacted by whether they are part of communities, what kind of influence their communities have on them, whether their communities fulfill their needs, and whether they have emotional connections with others in their community. McMillan and Chavis set the foundation for research, processes, and initiatives that focus on students' lived experiences in community and not just the practicalities of community structures.

Tinto, Astin, McMillan, and Chavis are contributors to the overwhelming amount of retention theories that exist. These theories note that not every student is the same, and so they stay or leave an institution for a variety of reasons. However, the theories noted above provide institutions with a well-rounded view of what is important to the student. Based on these theories and others, there are a variety of individual factors that influence why students stay at or leave institutions.

Retention Factors

A variety of factors influence student success and, in turn, influence whether a student decides to stay at or leave an institution. It is hard to know which factors are most influential for specific students, so this section will address what current research indicates is influential for retention and persistence.

Pre-Matriculation Data

The earliest factors that influence students is what they experienced or did in high school or at their previous institution. This experience is collected as pre-matriculation data, which is collected from the student before they begin their first semester. Most of this information is gathered during the admissions process and is used when determining whether a student should be admitted into the institution. Institutions admit students for a variety of reasons that are mostly tied to goals the institution possesses. Information gathered during the admissions process that is used to determine persistence includes, but is not limited to, socioeconomic status, high school GPA, and ACT/SAT scores (De Clerq et al., 2018; Saunders-Scott et al., 2018). In one study involving 165 undergraduate students, the association between ACT scores and cumulative college GPA was statistically significant ($p = 0.04$) (Saunders-Scott et al., 2018). This means that the students' ACT scores successfully predicted their college GPA.

Since these data points noted above have been used to predict student success, institutions may use this information in a variety of ways. For instance, this data is used to place students in categories known or unknown to the student, which influences how the institution serves the student. These influences are geared towards supporting academic success and student persistence. For example, if a student is admitted into an institution but has a low GPA, they may be required to take a college learning strategies course or be put into a cohort model.

This information is not just used by institutions, but it is also used by students as they prepare for school. Seventy-two percent of the students revealed in one study mentioned "readiness" as a theme that assisted them in their transition (De Clerq et al., 2018). This readiness includes the knowledge they were assessed on through the ACTs/SATs (De Clerq et al., 2018).

Institutional Factors

Once students arrive on campus, some of their interactions or experiences are directly connected to the institution. For example, interactions with faculty, staff and other students are very impactful (Bauman et al., 2019; Purdie & Rosser, 2011). These interactions can include but are not limited to hall mates, peer tutors, advisors, faculty, student government representatives, and dining services workers. When interviewed, students repeatedly indicated that positive interactions with staff and faculty make them feel known. This feeling of being known helps establish the student's sense of belonging. In one study, 57% of the students indicated that faculty and staff support helped them succeed academically (Bauman et al., 2019). Students living on campus interact with other students and staff at a higher rate than commuter students, which helps increase their engagement with the institution at large (Burger & Naude, 2020). The more positive interactions students have with individuals connected to the institution, the higher their institutional identity and sense of belonging will be.

Interactions students have outside of the institution have a large impact on them as well (Bauman et al., 2019). These interactions include, but are not limited to, their experience in the local community, at work, with their family, and church. These interactions, whether positive or negative, are out of the control of the institution and impact the student's overall college experience.

Student engagement, another common retention factor, is when a student actively initiates an interaction with the institution. Institutions provide students with opportunities, but students must try to partake in the opportunities. Trowler and Trowler (2010) go as far as to say that the importance of student engagement is "no longer questioned" because the more the student purposefully interacts with the institution the better. (Trowler & Trowler, 2010, p. 9).

Included in these institutional interactions are mentoring relationships. Mentoring is when a student has a relationship with a more experienced peer or faculty member that helps the student to grow and gain insight. Research shows that students involved in a mentoring relationship are more likely to succeed (Palmer et al., 2011). Students can find peer or faculty mentors organically or through an organized institutional program.

Institutions can use various tools to assess student interactions and engagement, with most tools being surveys students take. Some institutions create their own survey, while others use research-based instruments, like the National Survey of Student Engagement (NSSE) and the Community College Survey of Student Engagement (CCSSE) (McCormick et al., 2013). The NSSE is distributed in the spring semester to first-year students and seniors, while the CCSSE is sent during the spring semester to any student.

The data collected from the students help institutions adjust their policies and programs. If an institution uses the same tool for several years, they can see results over time that can indicate trends or changes in student behavior. Other retention factors, like involvement in research, satisfaction with their degree program, and purposeful feedback from faculty relate to students' academic lives.

Academic Life Factors

Institutions provide research opportunities for students, and a student's involvement in research has been proven to increase retention and persistence (Bowman & Holmes, 2018). A student's satisfaction with their degree program or their classes has been shown to positively impact self-efficacy and motivation (van Rooij et al., 2018). The more interested a student is, the more motivated they will be to take ownership of their learning (Burger & Naude, 2020). Consistent and honest feedback from professors has also been shown to positively impact student success and outcomes (Picton, 2018). This feedback can include, but is not limited to, feedback on assignments, personalized tips and strategies during faculty office hours, and quick, thoughtful responses via email.

Institutions can measure academic factors in various ways. They can collect and analyze course grades, feedback from end of course surveys, academic skill assessment tools, and institutional created surveys (Saunders-Scott et al., 2018). The data from the various methods create a picture to help institutions make decisions. Non-cognitive variables, the personal and social aspects of an individual, must be considered.

Non-Cognitive Factors

Institutions should not just focus on a student's cognitive growth but should work towards increasing non-cognitive skills, so students are fully prepared for the workforce (Yi et al., 2018). Non-cognitive variables include, but are not limited to, students' sense of belonging, self-efficacy, self-concept, motivation, and interest. Studies have shown that when institutions measure non-cognitive variables and make decisions based on the variables, student success increases (Boyd et al., 2020), while others reveal that non-cognitive factors do not always outweigh cognitive factors (Willems et al., 2018).

Research has shown that while academic success is vital for students, their sense of belonging is just as important (Picton et al., 2018). A student's sense of belonging is their feeling of being accepted, valued, included, and encouraged by others in their community (Boyd et al., 2020). Emotional connections play a significant role in a student's sense of belonging. This sense of belonging has been shown to positively and negatively influence students' emotional and physical well-being (Boyd et al., 2020). While in college, a student's community could include their class, residence hall, fraternity/sorority, and/or academic school.

Students leave institutions when they feel disconnected from the community and are overwhelmed (Yan & Sendall, 2016). Knowing that a student has other individuals encouraging them and wanting them to succeed increases their own desire to succeed (Matthew et al., 2018;

Mkonto, 2018). The more students feel like they belong, the more they are satisfied with their experience, and the more likely they are to persist towards degree completion (Al-Sheeb et al., 2018; Yan & Sendall, 2016).

One study involving 522 students from an Association to Advance Collegiate Schools of Business (AACS)-accredited business school used several non-cognitive variables as data points that were measured. The variables included interest in course, certainty of major, and number of doctor visits. The data was put into predictive analytics in an effort help faculty deliver course content more efficiently and interact with students more purposefully. The data was collected from various databases, as well as from a survey the students participated in. The study showed an increase in grades by 9% when the faculty used the predictive analytics to proactively reach out to students (Yi et al., 2018).

Another non-cognitive variable of note is self-concept. A student's self-concept is made up of their views and beliefs about who they are. The more students understand themselves and put to words who they are and what they are doing in school, the higher the chance the student will be successful and continue towards degree completion (Boyd et al., 2020).

Intrinsic motivation also impacts why students do what they do. It is an individual's drive to accomplish something without an external reward. A lack of intrinsic motivation to continue their education has been shown to directly correlate with a student leaving the institution (Al-Sheeb et al., 2018). A similar factor to intrinsic motivation is grit. Grit is where an individual's passion and perseverance meet (Duckworth et al., 2007). While grit is a new non-cognitive trait, researchers have tried to make connections between grit and student success. Some studies found positive correlations, while other studies find no correlations (Bazelais et al., 2016; Weisskirch, 2018; Wolters & Hussain, 2015). The varied conclusions involving grit and retention, or academic success reveal that more research should be conducted in order to generalize the relationship.

A study from the University of North Carolina revealed that sub scores of grit were successfully predicting grade point averages. The scores were obtained from the student via a survey, which they used for analysis. When the grit sub scores were added to the model, which included other variables like gender, high school GPA, highest test score, and first-generation college student status, the variance increased by 5.3% ($p<0.001$), which significantly increased the accuracy of the model (Akos & Kretchmar, 2017).

Institutions can measure non-cognitive variables through surveys and research-based tools. Surveys allow students to self-report their motivation, interest, sense of belonging, self-efficacy, self-concept, and more. The results from the surveys or assessments will show institutions where the students are and can help inform decisions. The use of surveys or assessments to collect data, however, is contingent upon first, the students completing it, and second, the students giving honest answers.

A study in Belgium conducted in 2016 and 2017 measured self-regulation, processing speeds, prior knowledge, and academic achievement in first-year science, technology, engineering, and mathematic (STEM) students. The students were surveyed with the questions leading the researchers to certain scores for each category measured. The model used in the study only accounted for 27% of the variance with most of the non-cognitive variables not being statistically significant (Willems et al., 2018).

Academic Success

The main reason a student attends college is to earn a degree. However, the journey towards degree completion and academic success looks different for each student. Some researchers believe that academic success can only be measured quantitatively through assessments and tests (Burger & Naude, 2020). Others believe that academic success can be holistic and encompasses every aspect of a student's academic experience (Burger & Naude, 2020). For this paper, academic success is defined as when students achieve their academic goals, thrive in all their spaces, and complete the required course work for their degree completion. Studies show that students believe academic success is closely intertwined with their satisfaction with the overall student experience (Al-Sheeb et al., 2018).

Because all students and their academic goals differ, the factors that contribute to or hinder a student’s academic success are different. The retention factors above contribute to academic success, as well, but there are additional factors that impact academic success. These academic success factors can be categorized as student-related variables and external variables.

Student-Related Variables

Student-related variables include their socioeconomic status, demographic attributes, academic skills, self-efficacy, language efficiency, physical and mental well-being, and their definition of success (De Clercq et al., 2018; Burger & Naude, 2020; Li et al., 2010). Academic skills are abilities a student possesses to assist their learning process. These include study skills, test-taking strategies, and note-taking. Language efficiency is important for students who are attending an institution that uses a language that is different than their first language. The largest population affected by language efficiency is international students.

It is important for the student to be able to define what success is for them. Success may look like getting all A’s, having a good work and school balance, being part of the student body association, and more. Whatever the student sees as success will help navigate them through their academic life. Intrinsic and extrinsic motivation also play a massive role in their academic success (Coetzee, 2011; Li et al., 2010).

Student related variables can be collected and analyzed by the institution in order to increase engagement, academic success, and retention. Demographic information about students is stored on their student file, which can be compiled and analyzed to find trends. Assessments can be used to measure academic skills and motivation. The results of the assessments can be used to inform decisions.

Assessments like the Self-Description Questionnaire III (SDQ III) developed by Herbert W. Marsh and Rosalie O'Neill in 1984 can be used by institutions to measure student related variables. The SDQ III was designed and has been proven over the years to measure 13 dimensions of self-concept (Marsh & O’Neill, 1984). One study used the SDQ III to measure the connection between being abused as a child and self-concept in college students, which showed statistical significance ($p<0.0015$) (Coetzee, 2011). The results of this study contribute to literature that helps institutions understand their students better.

External Variables

External factors influence a student's academic success that they can, to an extent, control. External variables that support or hinder academic success include but are not limited to social supports, engagement in research, familial expectations and support, access and use of campus resources, living arrangements, outside responsibilities, and academic engagement/class attendance (Bauman et al., 2019; Burger & Naude, 2020; Broos et al., 2020; Li et al. 2010; Martin et al., 2020; Matthews et al., 2018). When a student has a community that supports their academic endeavors, they are more likely to succeed in their courses (Matthews et al., 2018).

Engagement in research not only helps students take what they are learning and put it into practice, it likely connects students to supportive faculty members (Burger & Naude, 2020). A student's living situation can greatly impact academic success. Depending on who the student lives with and how they are living can create a healthy or unhealthy environment for the student as they pursue their degree. Students who attend class have better grades and are more likely to continue towards degree completion (Burger & Naude, 2020). These external factors could be more difficult for institutions to measure. Institutional surveys or tools like the NSSE measure certain aspects of the external factors that impact student success.

First-Year Experience

Through the last 50 years of retention research, it is apparent that the first year, and even the first several weeks, are critical for students (De Clercq et al., 2018; Larsen et al., 2019; Upcraft & Gardner, 1989; Yan & Sendall, 2016). The more a student feels successful in those first several weeks or months at the institution, the more likely they will persist into their second year (van Rooij et al., 2018). Students are most likely to leave an institution between their first and second years, which is likely a result of having a challenging first year (Purdie & Rosser, 2011). Research shows that students experience positive and negative emotions during their transition to college (Liversage et al., 2018). No matter how prepared students may feel when arriving on campus, they will likely feel nervous and lost at some point during their transition (Bauman et al., 2019). The first year of college is full of significant adjustments. These adjustments or challenges include financial stressors, the need for precise time management, new and challenging academic expectations, new social structures that must be navigated, and more (Broos et al., 2020; De Clercq et al., 2018; Mkonto, 2018; van Rooij et al., 2018). To mitigate the challenges, many institutions have targeted and purposeful interactions with their first year-students.

First-Year Experience Initiatives

To support first-year students and maximize their success, institutions implement interventions and initiatives that include but are not limited to summer orientation events/courses, introductory courses, and seminars (Al-Sheeb et al., 2018; Culver & Bowman, 2020). Orientations usually take place before students begin classes, whether that is during the summer or the week before classes start. Orientation programming is centered around getting the student acclimated to life on campus. Introductory courses are general education college courses that students take that covers content that will help the student succeed. Seminars are often not-for-credit courses but are workshops that cover a variety of topics. These initiatives help provide equal opportunities for all students to succeed, no matter their high school GPA or other determining factors that classify them as at-risk for dropping out and leaving the institution (Culver & Bowman, 2020). Institutions use these initiatives as an opportunity to introduce students to all the support services available (Thakral et al., 2016). Studies show that students are most satisfied with their first-year experience when their courses connected them with other students, increased their motivation, and improved their academic skills (Al-Sheeb et al., 2018; Culver & Bowman, 2020).

These initiatives likely produce purposeful interactions that help students navigate their transition, shape how students persist towards degree completion, lay a foundation of success that impacts their future studies, and introduce them to faculty and other students (Meehan & Howells, 2018; Mkonto, 2018). Personal interactions with faculty and staff during the first few weeks help students establish realistic expectations of themselves and the institution

(Larsen et al., 2019; Upcraft & Gardner, 1989) and increase the students' sense of belonging (Picton et al., 2018). Programming that introduces students to their academic disciplines increases their sense of belonging and may motivate them to persist into their second year (Mkonto, 2018).

Peer support during the first year is essential, so institutions plan events and programs to foster a sense of community between first-year students (Palmer et al., 2011). A student who is the first in their family to attend college has a more challenging time understanding processes and expectations (Liversage et al., 2018). They also have a hard time navigating their independence when they feel dependent on others to help them make sense of their experiences (Liversage et al., 2018). While all students fear failing, it is more evident in first-generation college students, which can positively and negatively impact their motivations (Liversage et al., 2018).

These first-year initiatives are evaluated and assessed using satisfaction surveys, end of course surveys, and even first-year student retention rates. Institutions can also use tools like the NSSE that is sent in the spring to first year students. The data gathered can be analyzed and inform decisions.

Wellness

As students adjust to college life, essential aspects of their adjustment are their well-being and wellness. Wellness is the journey individuals go through towards their well-being. Gilah Benson-Tilsen and Rena Cheskis-Gold note that from their 20 years of research, wellness is now recognized as an essential focus for institutions as they help students integrate into the campus life (Benson-Tilsen & Cheskis-Gold, 2017). There are different dimensions of wellness, but this section will introduce and discuss physical wellness, as well as mental health in college students.

The transition to college can seem freeing for students, but this freedom can result in the adoption of unhealthy behavior (Hsu & Chiang, 2020). For many students, this is the first time in their lives that someone is not making their food and ensuring they are physically active, thus it is important for students to know how to make wise and healthy decisions (Sogari et al., 2018). Some students come from cultures or families that do not prepare them for a healthy college life (Upcraft & Gardner, 1989). These healthy decisions can help students establish healthy habits that will affect their behavior even after college (El Ansari et al., 2015; Upcraft & Gardner, 1989).

Mental Health

Mental health is imperative to discuss when evaluating college students. The Center for Disease Control (CDC) and prevention defines mental health as an individual's "emotional, psychological, and social well-being" (CDC, 2021). Since a student's mental health encompasses so much, good mental health is paramount to their overall wellbeing, and thus their academic and college success.

Survey results from the American College Health Association indicate that aspects of college students' mental health are steadily declining (American College Health Association, 2021, 2019, 2015, 2011). For example, when asked about whether they have felt hopeless within the last 30 days, 9.1% of the students surveyed in 2011 said yes, 9.4% in 2015 said yes, and in 2019, 11.2% said yes (2021, 2019, 2015, 2011). A similar survey conducted in 2021 showed that 28.2% of the respondents indicated that they felt hopeless some of the time (2021). When asked about whether the student had felt lonely within the last 30 days, 13.6% of the students surveyed in 2011 said yes, 12.8% in 2015 said yes, and 14.2% said yes in 2019 (2019, 2015, 2011). When asked about feeling so depressed that it was difficult to function, 6.1% of the students surveyed in 2011 said yes, 6.8% in 2015 said yes, and 8.9% said yes in 2019 (2019, 2015, 2011). When asked about whether they felt overwhelming anxiety within the last 30 days, 11.7% of the students surveyed in 2011 said yes, 12.6% said yes in 2015, and 14.1% said yes in 2019 (2019, 2015, 2011). Each of the examples above are evidence of the declining mental health in college students.

In 2007, a review of surveys from the World Health Organization from 28 countries found that the age of onset (AOO) for most mental health disorders, including impulse control disorders and substance abuse disorders, occurs before 25 years of age (Kessler et al., 2007). This indicates that it is very possible for college students to experience their first episode of a mental health disorder while they are in college, or right before attending college.

A variety of factors can impact an individual's mental health as seen in a study published in 2012. Results of the study that evaluated surveys found that healthy coping mechanisms, strong spiritual identity, social engagement, and institutional identity were just a couple of factors that positively impact a college student's mental health (Byrd et al., 2012). The results also found that work/life issues interfering with school, negative perceptions of campus climate, suicidal tendencies, and perceived limited interactions with faculty were factors that negatively influenced a student's mental health (Byrd et al., 2012). Some of these factors will be discussed in detail below as research supports these claims.

As discussed earlier, the adjustment from high school to college is not always easy. This adjustment can significantly impact a student's emotional well-being and mental health. Stress is the tension that individuals experience when demand or challenge arises (Dusselier et al., 2005). It is a common emotional tension that all individuals feel, but first-year college students may experience stress levels they have never felt before. Physical and emotional demands, including over-commitment, relationships, finances, academic obligations, family problems, etc., contribute to a student's stress levels (Dusselier et al., 2005; Sokratous et al., 2013). Stress causes emotional and physical responses, like tiredness, sleep disturbances, headaches, change in appetite, and depression in college students (Black, 2018; Dusselier et al., 2005; Deckro et al., 2002). These symptoms can cause an inability to deal with the root of the stress, suicidal ideation, and a sense of hopelessness (Dusselier et al., 2005). Heightened stress levels can compromise a student's health, as it impacts their physical wellness (Deckro et al., 2002). It has also been shown that stress harms academic performance and eating habits (Dusselier et al., 2005; Saunders-Scott et al., 2018; Sogari et al., 2018).

Stress can also lead to depression, common among college students (Sokratous et al., 2013; Taliaferro et al., 2009). Stressful life events directly correlate with depression in college students (Sokratous et al., 2013). These events include family or friend’s death, sexual assault, academic overload or demands, financial pressures, new job, new relationships, and more. (Cordero, 2020; Sokratous et al., 2013). Depression, just like stress, causes a variety of physical and emotional problems, such as lack of motivation and concentration, lower brain processing, low happiness scores, mood swings, and lower feelings of self-worth (Sokratous et al., 2013).

According to Yong-Ku Kim, major depression disorder (MDD) is when depression symptoms last 2 weeks or longer (2018). Depression and its symptoms can impact a student's ability to learn and succeed in college. Students with MDD miss more classes, and one study demonstrated a mean difference of .25 lower GPA than their peers who were not depressed (Hysenbegasi et al., 2005; Sokratous et al., 2013). There is also evidence that depression dramatically impacts an individual's eating habits (Ivezaj et al., 2010). Students experiencing depression have been known to binge eat at a higher rate than those that are not depressed (Ivezaj et al., 2010).

Measuring the mental health and emotional wellness of college students can be accomplished in a variety of ways. First, institutions can survey their student population with an in-house survey. Institutions can also use research-based tools that have proven effectiveness. One example of a helpful tool is the Perceived Wellness Survey, which measures the perceived wellness of the individual taking the survey (Adams et al., 1998). Another tool is the Patient Health Questionnaire-9, which can help diagnose MDD (Spitzer et al., 1999). It should be noted that many of these tools and assessments require self-reported information.

One study used a survey sent to first-year students to assess the student's likelihood of becoming depressed. Sixty-one percent of the population took the survey and the results indicated that 1 in 4 of the students predicted to become depressed, did in fact become depressed (Ebert, 2019). Another study evaluated whether alcohol consumption and/or alcohol consequences could predict depression in first-year female college students. The results indicated that while alcohol consumption was not related to depression, the prevalence of alcohol consequences was related to depression ($p>0.05$) (Rosenthal et al., 2018).

Physical Wellness

Physical wellness is essential for students to understand and pursue. It encourages cardiovascular and overall health through regular activity, knowledge about the importance of nutrition, and active choices that support self-care (Upcraft & Gardner, 1989). Healthy behavior for college students should include making wise food choices, exercising, and good sleeping habits (El Ansari et al., 2015; Hsu & Chiang, 2020; Sogari et al., 2018).

The Freshman 15 is a common expression in the United States that refers to the weight students gain during their first year in college. While research does not support the fifteen-pound claim, it does show that first-year students gain about 5% of their body weight (Goldstein et al., 2015). The Freshman 15 brushes the surface of the physical and emotional impact the first-year adjustment has on students.

Unhealthy behaviors in college students include lack of sleep, poor quality of sleep, unhealthy dietary decisions, lack of regular exercise, binge drinking or eating, skipping meals, smoking, and the use of illicit drugs. Students make these decisions for a variety of reasons; however, most reasons are linked to peer pressure and an unhealthy environment (Goldstein et al., 2015). Affiliations with Greek life, nonsubstance-controlled housing, lack of accountability for classroom attendance, and more greatly influence a student's decision to partake in unhealthy behavior (El Ansari et al., 2015; Goldstein et al., 2015). These unhealthy behaviors negatively impact students' cognitive processing ability, which dramatically impacts their academic success (Ferreira-Pego et al., 2020).

The importance of physical activity is well known to all, but it is vital for college students to prioritize early on in their college careers. Physical activity has been shown to positively impact students' emotional well-being and even academic success (Taliaferro et al., 2009; Bellar et al., 2014). A research study from a university in Louisiana found that the more a student participated in aerobic exercise, the higher their GPA was ($p < 0.001$) (Bellar et al., 2014).

Another study evaluated the relationship between BMI, gender, and course grades. The study found that the relationship between BMI and course grade was statistically significant ($p = 0.001$), but gender did not have a relationship with course grade (Anderson & Good, 2017).

Exercise also promotes a good self-image and can protect against suicidal tendencies (Taliaferro et al., 2009). A lack of exercise can really impact weight and future health (Sogari et al., 2018).

Healthy eating is closely linked with physical activity, and students should know that both are important (Sogari et al., 2018). Healthy eating and regular physical activity reduce the likelihood of students developing diet-related diseases, like high cholesterol, as an adult (Ferreira-Pego et al., 2020; Sogari et al., 2018; Upcraft & Gardner, 1989). Eating behaviors include food selection, preparations, portions, and eating habits (Ferreira-Pego et al., 2020). These behaviors can be healthy or unhealthy. Research shows that Americans, including college students, know that eating healthy is essential (Watanabe-Ito et al., 2020). However, they do not consume the recommended number of fruits and vegetables but consume higher than the recommended number of sugars and processed foods (El Ansari et al., 2015; Sogari et al., 2018).

While knowledge about the importance of healthy eating is there, turning that knowledge into action is difficult. Individuals may not know how to eat healthy given their circumstances, such as having a lack of access to healthy food as a child and knowing how to purchase and store healthy food (El Ansari et al., 2015). The most recent American College Health Association-National College Health Assessment surveyed 70,087 undergraduate students. Sixty-five percent of the individuals drank at least one sugary drink every day of the last 7 days. Twenty-one percent of the individuals ate at least three servings of fruit per day for the last 7 days, while thirty-three percent of the individuals ate at least 3 servings of vegetables per day for the last 7 days (2021). These results show that students drink sugary drinks often and may not eat many fruits and vegetables.

Eating Habits

Breakfast is the first meal of the day and prepares the body to work for the next 15-17 hours or until sleep. Breakfast should provide the body with the nutrients it needs to start the day (Kang et al., 2018). The consumption of breakfast has been shown to improve a student's recall, test anxiety, happiness, learning abilities, and memory skills (Akbari et al., 2020; Kang et al., 2018; Ogungbayi et al., 2020; Trockle et al., 2000). Different types of food, like carbohydrates, high-fats, and protein-rich foods, consumed for breakfast support brain functions that students use while performing academic-related work (Brandley et al., 2020).

However, skipping breakfast is a common and unhealthy decision college students make for various reasons, such as time constraints, sleep, and finances (Kang et al., 2018). Some students also indicated that they wake up and are not hungry and thus do not eat (Kang et al., 2018). Skipping breakfast can negatively impact the body with consequences that may include increased diet-related diseases and cardiovascular diseases (Kang et al., 2018). Studies have also shown that students who smoke, consume soda and alcohol, and partake in other unhealthy behaviors eat breakfast irregularly, which is not beneficial for their bodies and academic success (Kang et al., 2018). Students who skipped breakfast (M 2.80, SD 1.02) also recorded lower happiness scores than those that indicated they ate breakfast (M 3.21, SD 1.02) resulting in a statically significant difference in happiness ($P<0.05$). (Kang et al., 2018).

Binge eating and drinking (consuming large amounts in a small period) are common habits in college students (Phillips et al., 2016). These habits are concerning because the college-aged population is at a higher risk for developing diagnosable eating disorders (Phillips et al., 2016). A study of over 100 female college students from a large US university was evaluating the relationship between stress, coping, and binge eating. The results indicated that stress and binge eating had a significant positive correlation ($p<0.001$) (Sulkowski et al.,2011). The study also indicated a significant positive correlation between binge eating and emotional coping ($p<0.001$), stress and emotional coping ($p<0.001$), and binge eating and avoidance coping ($p<0.01$) (Sulkowski et al.,2011).

Another study in the Journal of College Student Development found a connection between binge eating and attachment insecurities (Han & Lee, 2017). This study included over 1,000 students from a mid-western university in the United States and noted that students who had trouble with emotional regulation and who did not have their basic psychological needs met were more likely to binge eat ($p = 0.02$) (Han & Lee, 2017).

Studies also show that students' finances can impact their eating habits (El Ansari et al., 2015; Goldstein et al., 2015). Unhealthy foods are usually cheaper, easier to carry around, and do not expire quickly. A study of students from a variety of community colleges in the US investigated the relationship between food insecurity, living situations, and college GPA. Students who lived alone or with roommates were more likely to be food insecure as compared to students who lived with family members ($p = .007$) (Maroto et al., 2015). A binary regression analysis indicated that there was a significant relationship between food security status and GPA ($p = 0.042$) (Maroto et al., 2015). Students in the lower tier GPA are more likely to be food insecure than those in the highest GPA tier (Maroto et al., 2015). Time is also a factor in making nutritional choices, whether students do not have time to eat breakfast at all, or they have a time constraint that does not allow them to make or eat a well-rounded meal (El Ansari et al., 2015).

Students at a military college were involved in a study that assessed student stress levels and their eating habits. The study used an experimental group and a control group. The experimental group had a goal of eating more fruit and colorful food where the control group did not have the goal of eating better. Both groups took a survey that measured their stress and both groups logged the food that they ate. Upon analyzing the data, both groups reported the same amount of stress, however, the group that had the goal of better eating ate more fruit ($p = 0.026$) and colorful food ($p = 0.037$) (Moosman, 2017). It was clear that the stress negatively impacted the students that did not have the goal to eat better food ($p = 0.033$), while the students with the goal were able to combat the impact stress might have on their eating habits (Moosman, 2017).

One institution in Tokyo wanted their students to be more aware of their eating habits. They then evaluated the use of a social media type mobile application and students' interest in their eating habits. The students would track their meals, but since it was a social app, students would see what their friends were tracking and vice versa. The results indicated that over time students' interest in their eating habits increased ($p < 0.001$) and that they enjoyed the social aspect of the app (Watanabe-Ito et al., 2020).

A study consisting of young women evaluated the relationship between adverse life events, depressive symptoms, and comfort eating. Several different questionnaires were used to collect the data and upon analysis, young women with an adverse life event, like moving to a new place, evidence of comfort eating, and depressive symptoms, successfully predicted stress in the participants ($p = 0.035$) (Finch & Tomiyama, 2015). This study revealed that certain eating habits in conjunction with other factors, like moving to a new place, can predict whether young women are stressed (Finch & Tomiyama, 2015).

In order to assess the health of students on an individual level to see a change in habits, an institution in Lisbon evaluated the change in the students' eating habits before and after they transitioned to school and living on their own. The researchers collected information from the participants through a survey and analyzed the data, which revealed that the eating habits of the students after beginning school did change in certain areas (Bárbara & Ferreira-Pêgo, 2020). For example, they consumed less fish ($p = 0.001$) and legumes ($p = 0.002$) (Bárbara & Ferreira-Pêgo, 2020).

These studies from all over the world on eating habits and their influence on students indicate that measure physical wellness and mental health is imperative for higher education institutions.

Dining Services in Higher Education

College and universities' dining services offer students, faculty, and staff dining options on and/or near campus. These services offer clean and safe spaces for individuals to eat their meals (Ho & Madden-Hallett, 2020). The mission and vision behind most dining services include providing quality food, food services, and nutritional education through dining halls and retail dining locations. Schools also use their dining services to expand upon other institutional initiatives. For example, dining services can assist with cultural engagement by offering international cuisine and education. They can also help with sustainability goals by composting leftover food and cooking with food from local farms or businesses.

Institutions offer dining plans students purchase in order to interact with the dining services. Students select a dining plan that suits their needs, and then all their dining interactions are based on the dining plan. Since students purchase these plans and the dining services spend money and produce revenue, dining data is tracked by the university. This data could include when a student interacts with dining services and what they purchase. More details on dining data will be discussed in the sections below, as this study will work to connect dining data to retention and academic success.

Many college and university campuses have different dining options, like a sit-down cafeteria, coffee shop, and/or convenient store-type option. All these different options allow for students, faculty, and staff to buy and consume food. Studies show that it is important for individuals to eat meals together (Sobal & Nelson, 2003). When individuals eat a meal with other individuals, whether with family, friends, coworkers, neighbors, it is called a commensal meal (Sobal & Nelson, 2003). When eating with others, it is common for the individuals to establish a new relationship or grow an existing relationship (Danesi, 2012). As Han and Lee discussed at the end of their study, college administrators can support students' emotional and physical well-being by encouraging students to sit down and eat together (Han & Lee, 2017). College dining services and the interactions students have while eating, are important for their emotional and physical well-being, which can support their academic success and persistence in college.

Big Data in Higher Education

Many advancements in information technology and research technology were made through college and university research divisions in the 1960s. Because of this higher education has been integrating technology into its operations (Picciano, 2012). During the 1960s, 1970s, and 1980s, technology was mostly used to store academic and administrative records. After the Internet emerged, technology use in higher education began to shift. Currently, institutions use data to make decisions that impact the student experience, faculty experience, and more.

Big data is a new field of research that is prominent in the business, government, and health care sectors (Daniel, 2015). This field of research uses data to make decisions. As institutions attempt to increase student success and retention, using data to drive decisions has increased. Since there is no one-size-fits-all approach to retention in higher education, institutions can use data from their very own student population to meet specific needs (Blanchard, 2018). Collecting and analyzing student data allows institutions to interact with students in a more purposeful manner. No matter the size, it can be difficult for institutions to personalize purposeful interactions without student data driving the design of these interactions (Patel, 2019). Personalized purposeful interactions significantly impact the student experience and student outcomes.

Depending on the type of data, data can be collected and stored in real or near-real time, and thus, can be analyzed quickly (Picciano, 2012). Once collected, the data is analyzed, which means it can be studied in order to draw conclusions (Picciano, 2012). The way the data is analyzed may depend on the purpose of the data analytics. When using Big Data, higher education institutions must take into consideration the cost and labor required for data collection, storage, analysis, accuracy of analysis, and ethical concerns. The cost of collecting and storing data can be expensive if institutions do not already have processes in place for data collection and storage (Daniel, 2015). The collection and analysis of data can also be expensive through the purchase of software or in paying employees to do the analysis (Daniel, 2015). Data analysis is only as good as the data itself, so institutions usually must sift through data and establish a collection process in order to ensure accuracy (Rajni & Malaya, 2015). As for the ethical concerns when using student data, it is suggested that institutions be as transparent as possible to avoid the wrongful use of data (Daniel, 2015).

Educational Data Mining (EDM) is "an area of scientific inquiry. EDM is concerned with the analysis of largescale educational data, with a focus on automated methods" (Baker & Inventado, 2014, p. 61). Since EDM focuses on automated methods, the data is collected and put into an algorithm that is used to analyze the data. Commonly used EDM methods include predictive analytics, regressions, factory analysis, and more (Baker & Inventado, 2014). Regression is a statistical process that explores the relationship between two variables, while predictive models seek to use current and/or historical data in order to make predictions about the future (Daniel, 2015). Baker and Inventado note that predictive analytics can be used to support interventions or make outcome predictions (Baker & Inventado, 2014).

Similarly, Learning Analytics (LA) is used to investigate learning and teaching (Nguyen et al., 2020). LA collects and stores data from learners, which then allows the learner or faculty to analyze the data to make decisions. The main difference between EDM and LA is the fact that EDM data is analyzed through automatic systems, whereas LA data is analyzed through human judgement (Baker & Inventado, 2014). LA is organized and presented in such a way that the individuals can look at the information and make decisions. This organized view of data is frequently called a dashboard. Students who are struggling can use a LA dashboard to find areas of improvement (Nguyen et al., 2020). Broos et al. found that students' use of dashboards early in the academic year impacted their academic achievement later in the academic year. (Broos et al., 2020).

LA analytics can help faculty assist students, as well. A multi-methods study published in 2019 that involved 59 faculty members across nine different courses found that the LA tool confirmed their suspicions of a struggling student. The LA tool also alerted them to a struggling student that they would not have noticed otherwise (Herodotou at el., 2019). Faculty from this study noted that the data helped them be more proactive with students (Herodotou at el., 2019).

Academic Analytics (AA) is part of EDM since it is used to identify patterns, such as dropout rates, through automated analytics (Nguyen et al., 2020). The use of AA helps administration view students through a different lens. While LA is faculty and student facing, AA is mostly used by administrators and policy makers (Nguyen et al., 2020). Data collected through AA can be coded or put into an algorithm that can help predict student outcomes and success (Lipka, 2019). Common data points currently used include high school GPA, SAT/ACT scores, class attendance, institutional GPA, transfer GPA, test grades, missing assignments, mid-term grades, involvement in intramurals, completion of the FAFSA, the timing of course registration, and more (Cui at el., 2019).

Predictive analytics uses data to provide institutions with insight about the future that can drive decision making. Predictive analytics look at past trends and association that identify opportunities and risks for the future (Daniel, 2015). This type of data analysis can also use regression to reveal relationships between variables that may not have been known before analysis (Daniel, 2015; Daniel & Butson, 2013). Data points used, such as GPA, class attendance, and grades can be used in predictive analytics, as well. Studies, like one completed in the United Kingdom, reveal that the use of predictive analytics by faculty "positively predict students' pass and completion performance" (Herodotou, et al., 2019, p. 1298). While some of the faculty in the study were nervous about using the data, they noted that the use of the analytics did positively contribute to student success.

An initiative that institutions are implementing with the use of data are nudges. Nudges are targeted communications, emails, texts, and personal phone calls, which are sent to students and/or their family members in response to some data point. The point of the nudges is to communicate a call to action or change a behavior without coercion (Blumenstein, 2018).

One study indicated that personalized texts to students and their families with reminders about completing the FAFSA had a direct and positive correlation to persistence

(Castleman et al., 2016). Another research study from several institutions in Indiana used nudges to communicate assignments deadlines through an app the students could download. The study found that the reminders did increase assignment completion (Motz et al., 2021). Automated nudges did reduce the amount of missed assignments (Motz et al., 2021).

Another study with first-year students from West Virginia colleges and universities found that students who received the experimental texts attempted and completed more credits than the control group. These experimental texts included targeted information, reinforcement, and assistance for the students. The students in the experimental group were also more likely to remain enrolled throughout their first year (Castleman & Meyer, 2020).

Institutions can use their students' data to determine what type of nudge initiative would be most impactful. For example, an institution could use course grades data to determine which courses had low student grades and thus plan a nudge initiative for those courses encouraging students to attend tutoring sessions or the professor's office hours.

With the increased opportunity to use big data in higher education, institutions need take advantage of data to inform decisions. There are established uses of certain data points, like high school GPA and class attendance, in retention efforts, but there are data points, like dining data, that has not yet been thoroughly explored.

Dining Data

Researchers have started using dining data to assess wellness initiatives and the relationship between students' social interactions and academic success. Dining data is information collected about the interactions students have with the dining services offered at the institution. This information may vary from institution to institution, but can include time of interaction or purchase, amount of food purchased, type of food purchased, and amount of time spent in the dining location. This information is available in real or near real time and is not dependent upon the student self-reporting.

While there is not a wealth of studies that have used dining data, there are some studies that have evaluated the effectiveness of wellness initiatives and the relationship between social networks and graduation rates. Research from a university in Ontario over several years was published in at least two studies. The first study sought to use dining data to evaluate the effectiveness of new and current wellness initiatives at the institution. Part of the new peer-led wellness program included the distribution of special dining cards that could be turned in by students in exchange for free fruit or dairy products. During the time of the first study, almost 2,000 cards were turned in, which revealed to the institution that the program was effective, and students were choosing healthier food options (Matthews et al., 2014). In the second study published several years after the initial implementation, dining data in the form of special dining cards and net sales was used to evaluate the continued effectiveness of the wellness initiative. In this study, it was clear that healthier food was purchased more often on a weekly basis than before the program was implemented (Biden et al., 2018). The purchase of milk increased by 24% with the purchase of fruit increasing by 20% (Biden et al., 2018).

In the study assessing the relationship between social networks and graduation rates, the researcher used dining data in the form of dining hall swipes. The timing of the swipes and frequency of the swipes were used to establish social networks for students. The researcher assumed that if Joe and Jane swiped into the dining hall within one minute of each other on a consistent basis, that Joe and Jane were likely friends eating a meal together. Based on those established social networks, the study showed that students with an average amount of friends had a 74% chance of graduating on time, while a student with a standard deviation above the average had an 80% chance of graduating on time (Patel, 2019). The researcher also concluded that the number of friends a student had could be predicted within the first 8 days of the semester (Patel, 2019).

In conclusion, it is incredibly important for institutions to use data in order to make decisions that will best support student success, and ultimately retention and student persistence. The use of dining data in the form of weekly interactions may prove to be an informative area to study as it relates to GPA and retention rates.

CHAPTER THREE

METHODS

Introduction

There is no one reason a student stays or leaves an institution. A student's college experience consists of all their interactions, successes, failures, and more. These experiences influence whether students continue towards degree completion or not. Also, as big data grows in the field of higher education, institutions use a variety of data to inform decisions that impact the student and the organization. Commonly used data includes pre-matriculated information, such as high school GPA, class attendance, missing assignments, and college GPA. Physical wellness and mental health in college is important and can impact academic and college success. First-year students can have a difficult time adjusting to the freedoms in college, the rigors of the academic work, and more. Institutions mitigate these difficulties with a variety of initiatives that support social and academic success.

An aspect of the college experience that has not been researched much is the dining experience. While the interactions students have with dining services has not been noted as a retention factor, dining data may give insight into how students are doing physically and emotionally. A significant change in dining habits could be evidence of a larger issue that the institution can address and thus offer personalized assistance.

This study explored the relationships between the independent variables (average dining interactions per week and significant changes in dining habits) and the dependent variables (first-year retention and academic success). The relationship between dining data (in the form of weekly interactions and significant changes in dining habit) and retention as well as the relationship between dining data and academic success were be explored by using three different types of statistical tests. Academic success was determined by the students' semester GPA, while retention or student persistence was determined by whether the student enrolled in the next term. The research questions, setting and context, research design, and research procedures are detailed below.

Research Design

This research study was a non-experimental causal-comparative design. Since a causal-comparison investigates the effect, an independent variable has on two or more groups, this design was chosen in order to explore the effect dining data may have on retention and academic success (Salkind, 2010). Linear regressions, binary regressions, and chi-square tests were conducted to answer the research questions.

Research Questions

To explore the relationship between dining data and academic success and retention in first-year students, the questions below guided the study.

RQ1: What is the relationship between a student's weekly average dining interactions Monday through Friday and their academic success during their first and second semesters at a large private university?

RQ2: What is the relationship between a student's weekly average dining interactions Monday through Friday and their persistence into their second and third semesters at a large private university?

RQ3: What is the effect of a significant change in dining habits on a student's academic success during their first and second semesters at a large private university?

RQ4: What is the effect of a significant change in dining habits on a student's persistence into their second and third semesters at a large private university?

Null Hypothesis

$N_0$1: A student's weekly average dining interactions Monday through Friday has no relationship to their academic success during their first and second semester at a large private university.

$N_0$2: A student's weekly average dining interactions Monday through Friday has no relationship to their persistence into their second and third semester at a large private university.

$N_0$3: A significant change in dining habits does not affect a student's academic success during their first and second semester at a large private university.

$N_0$4: A significant change in dining habits does not affect a student's persistence into their second and third semester at a large private university.

Independent Variables

The independent variable for the first two research questions was the students' average weekly dining interactions Monday through Friday during their first (15 weeks) and second semester (15 weeks). The independent variable for the last two research questions was whether the student experienced a significant change in their dining habits. A significant change in dining habits was determined using ranges were created from the student's standard deviation.

Dependent Variables

The dependent variables for all four research questions are retention and academic success. Retention or student persistence was measure by whether they enrolled in the following semester. Academic success was measured by the student's institutional GPA for each semester analyzed.

Setting

The sample attended a private four-year institution located a mid-Atlantic state. The institution is in the suburbs with a vibrant and growing city located just fifteen minutes from campus. There were between 10,000 and 15,000 residential students with about 8,000 of the students living on the campus. The institution has over 20 NCAA Division I sports teams and a variety of club sports teams. There are more females than males on campus with a low non-traditional student population. Most of the student population comes from the East Coast, but over 70 countries are represented. The fall-to-fall retention rate at the university for 2018-2019 was seventy-eight percent. The most recent 6-year graduation rate for students that started in 2013 is fifty-two percent.

Population and Sample

The participants for this study were brand new incoming residential first-year students that did not transfer any credits and who lived on campus. Archival data was used since the participants started during the fall of 2016, fall of 2017, or fall of 2018. At this institution, all students living on campus are required to purchase a dining plan. Due to the criteria of being a new student living on campus, 3,112 students were included in this study. On-campus dining services for this institution include one large dining hall and more than ten retail locations.

Data Collection

Upon obtaining Institutional Review Board exemption, the data report was submitted. The data was de-identified archival data that already exists in the institution's data warehouse.

The institution employed a team of data analysts that were tasked with pulling and organizing the data in Excel that was formatted by the researcher. The report request was completed with accuracy two month after being submitted.

The archived data was pulled from directly student files and organized in Excel. NCAA Division I student athletes were excluded from the sample that included all new students who lived on campus during the designated semesters. The data collected for each student included the information below:

- Average weekly dining interactions for Monday-Friday of each week of their first two semesters (independent variable)
- High school GPA (demographic information)
- Institutional GPA for first their first three semesters (dependent variable)
- Gender (demographic information)
- Ethnicity (demographic information)
- Number of attempted credit hours for their first three semesters (dependent variable)
- Number of earned credit hours for their first three semesters (dependent variable)
- Housing assignment for their first three semesters (demographic information)
- Academic standing for first three semesters (dependent variable)

Data Analysis

Upon receiving the data in Microsoft Excel, the data was imported into SPSS 28. Data analysis involved descriptive statistics, linear regressions, binary regressions, and chi-square tests.

First, the average dining interactions students had Monday through Friday of their first two semesters were calculated. New variables were created that measured the average weekly interactions for the first semester (15 weeks) and second semester (15 weeks).

Second, the students were separated into groups of returned or not returned for each semester. This was completed by assessing the number of credit hours the student attempted and earned for their first three semesters. The attempted credit hours indicated the number of credit hours the student was enrolled in as of the second week of each semester. The earned credit hours indicated the credit hours that the student finished with a passing grade. If a student attempted credit hours, it was determined that they successfully enrolled in that semester. Retention was determined by whether the student enrolled in the semester following a successful completion of a semester. A new variable was created by giving students that enrolled in the following semester a 1 and the students that did not enroll in the following semester a 0.

Once grouped by retention status and after calculating the average weekly interactions, the data for the first research question were analyzed. After the assumptions were checked, linear and binary regressions were conducted.

For the last two research questions, significant changes in dining habits were calculated. A new variable was created that found the standard deviation (SD) for the student's first (15 weeks) and second semesters (15 weeks). This SD was unique for each student based on their own interactions, which ensured the students were being compared to themselves and not against other students.

In order to determine what a significant change in dining habits was, ranges were created. The first range was created by adding and subtracting the students' SD from their semester long average weekly dining interactions. If the student's weekly interactions fell outside of the range for 3 consecutive weeks, it was determined to have been a significant change in habit. A new variable was created that labeled the student as having a habit change. Students that had a drastic change in habit were labeled with a 1 and students that did not have a drastic change in habit was labeled with a 0.

The second range was created by adding and subtracting 1.5 SD from their semester long average weekly dining interactions. If the student's weekly interactions fell outside of the range for 2 consecutive weeks, it was determined to have been a significant change in habit. A new variable was created that labeled the student as having a habit change. Students that had a drastic change in habit were labeled with a 1 and students that did not have a drastic change in habit was labeled with a 0.

Once the drastic change in weekly dining interactions is created, the last two research questions were investigated through linear regressions and chi-square tests.

Limitations

The researcher has noted several limitations to the study that are outlined below.

- Since the dining interactions were pulled from student ID swipes, the researcher could not confirm that the student was the person that used the ID card.
- The type of meal plan purchased by the student was unknown to the research and may have influenced what students purchased.
- This study also only assessed the number of times a student interacted with dining services and not what the student purchased when

- The student’s housing location may impact their dining habits but was not fully investigated and controlled for in this study.

CHAPTER FOUR

FINDINGS

Overview

Students attend and leave college for a variety of reasons. For years, higher education administrators have been trying to determine why students leave and whether institutions can prevent the departure. Many students leave after their first full year at an institution and so schools have a variety of initiatives that attempt to mitigate student difficulties. Good physical wellness and mental health is imperative for academic success in college students. Poor habits, like skipping breakfast and not exercising, has proven to lead to academic difficulties. Additionally, with the advancements of technology in recent years, the use of data to help lower drop-out rates has increased. Data points like high school GPA, academic engagement, and others have helped institutions implement initiatives that seem to assist their retention efforts. Most data points used are accessible in real or near-real time but do not seem to represent a student's physical well-being and mental health.

This study assessed whether a student's weekly dining interactions can be used to predict academic success and retention. The section below outlines the details of the data analysis. The study used de-identified archived data from first-year residential students who began in 2016, 2017 and 2018. Several statistical tests were run to answer the outlined research questions.

Research Questions

In order to explore the relationship between dining data in the form of weekly interactions and retention as well as academic success in first year students, the research questions below guided the study.

RQ1: What is the relationship between a student's weekly average dining interactions Monday through Friday and their academic success during their first and second semesters at a large private university?

RQ2: What is the relationship between a student's weekly average dining interactions Monday through Friday and their persistence into their second and third semesters at a large private university?

RQ3: What is the effect of a significant change in dining habits on a student's academic success during their first and second semesters at a large private university?

RQ4: What is the effect of a significant change in dining habits on a student's persistence into their second and third semesters at a large private university?

Null Hypothesis

$N_0$1: A student's weekly average dining interactions Monday through Friday has no relationship to their academic success during their first and second semester at a large private university.

$N_0$2: A student's weekly average dining interactions Monday through Friday has no relationship to their persistence into their second and third semester at a large private university.

$N_0$3: A significant change in dining habits does not affect a student's academic success during their first and second semester at a large private university.

$N_0$4: A significant change in dining habits does not affect a student's persistence into their second and third semester at a large private university.

Descriptive Statistics

This study included 3,112 new students attending a large private four-year institution. There were 1,520 males and 1,592 females. The top three reported ethnicities were White (64%), Hispanic (7%), and African American (5.8%). The full participants' reported ethnicity can be seen in Table 1.

Table 1
Descriptive Statistics: Ethnicity

		Frequency	Percent
Valid	American_Indian_Alaska_Native	21	.7
	Asian	78	2.5
	Black_or_African_American	179	5.8
	Hispanic_Latino	216	6.9
	Native_Hawaiian_Pacific_Islander	4	.1
	Nonresident_Alien	93	3.0
	Two_or_more_races	100	3.2
	Unreported	433	13.9
	White	1988	63.9
	Total	3112	100.0

Grade Point Averages

Grade point averages (GPA) are calculated at the end of every semester. Table 2 reveals the amount of students that finished each semester and what the average GPA was. Students that left during the semester did not have a GPA. At least one student each semester failed, resulting in a 0.0 GPA, while at least 4 students received all As resulting in a 4.0 GPA. The average GPA increased as the students progressed from semester to semester and all three averages are considered in good standing at the institution.

Table 2
Descriptive Statistics: Average GPA per semester

	N	Minimum	Maximum	Mean	Std. Deviation
GPA for first semester	3108	.0000	4.0000	2.879228	.8482392
GPA for second semester	2900	.0000	4.0000	2.887401	.8982581
GPA for third semester	2508	.0000	4.0000	2.933485	.8519096
Valid N (listwise)	2494				

Retention

Retention is determined by the continued enrollment of students. Retention can be reported in several ways, but for this study, semester over semester retention rates were noted and year over year retention rates were noted. Semester over semester rates are determined by the number of students who start a semester and also enroll in the following semester. Of the 3,112 students that started their first semester, 2,898 started their second semester, resulting in a semester over semester retention rate of 93.12%. Of the 2,898 students that started their second semester, 2,508 started their third semester, resulting in a semester over semester retention rate of 86.54%.

Year over year retention rates are determined by the number of students who start one semester and enroll in the third semester. Of the 3,112 that started their first semester, 2,508 started their third semester, resulting in a year over year retention rate of 80.59%.

Dining Interactions

Table 3 displays the average number of dining interactions students had grouped by whether they stayed at the institution or left the institution. Using data from the first semester, students that enrolled in their second semester, on average, interacted with dining services over 9 times per week Monday through Friday ($M = 9.224$). Students that did not enroll in the next semester interacted with dining services, on average, over less than 8 times per week (Monday through Friday) ($M = 7.875$).

Using the data from the second semester, students that enrolled in the third semester, on average, again interacted with dining services over 9 times a week ($M = 9.411$). Students that did not enroll in their third semester, on average, interacted with dining services a little over 8 times a week ($M = 8.245$).

These numbers are insightful as they reveal that students who did not persist and ended up leaving the institution interacted with dining services less each week than their peers that stayed.

Table 3
Means of dining interactions

Started second semester	Mean	N	Std. Deviation
No	7.875	213	3.378
Yes	9.224	2848	2.985
Total	9.130	3061	3.033
Started third semester	**Mean**	**N**	**Std. Deviation**
No	8.245	390	3.117
Yes	9.411	2426	2.953
Total	9.250	2816	3.003

Housing Assignments

While a variety of housing options were available to students who lived residentially on the university campus, the options were categorized by access to a kitchen and no access to a kitchen. Table 4 reveals the breakdown for the housing assignments of the students during their first two semesters.

Students without access to a kitchen were in the majority each semester. Only 28% of the students in the study has access to a kitchen during their first semester, while 24% had a kitchen their second semester. This is important because students without access to a kitchen had to purchase food from dining services in order to eat on campus. Note that the missing data points represent students that moved off campus and no longer had a housing assignment.

Table 4
Descriptive Statistics: Access to kitchen

Housing Assignment for first semester			
		Frequency	Percent
Valid	Kitchen	878	28.2
	No kitchen	2230	71.7

	Total	3108	99.9
Missing	System	4	.1
Total		3112	100.0

Housing Assignment for second semester

		Frequency	Percent
Valid	Kitchen	773	24.8
	No kitchen	2056	66.1
	Total	2829	90.9
Missing	System	283	9.1
Total		3112	100.0

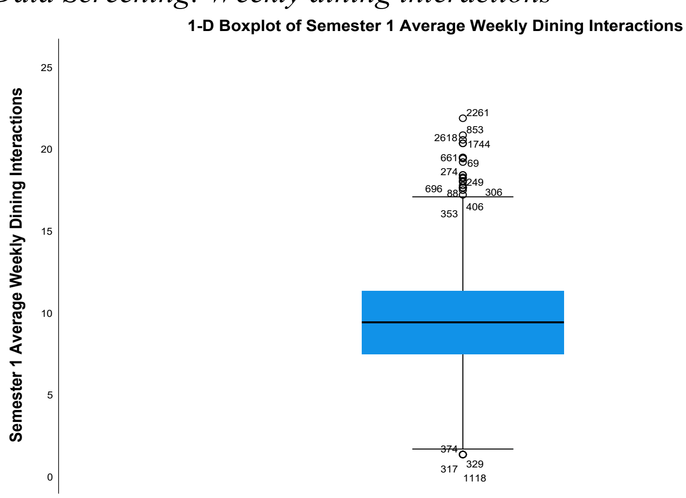
Results

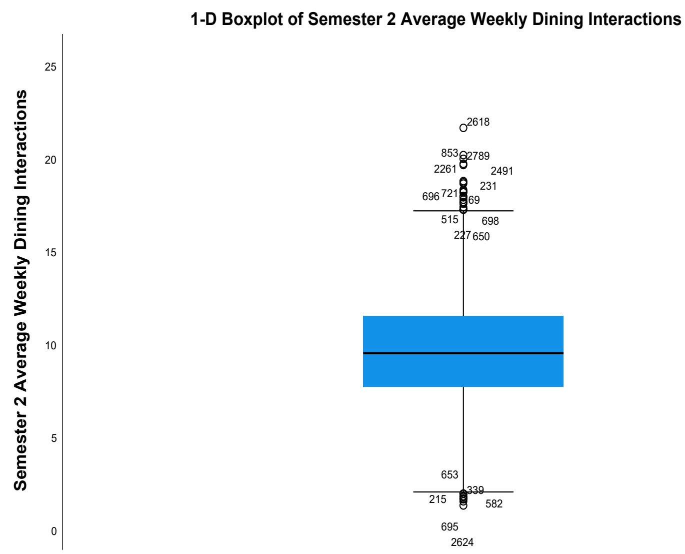
Data screening

When the data were received by the researcher, it was de-identified and thus specific students could not be identified. Before being imported into SPSS, the data were checked for inconsistency, irregularity, and outliers. Upon review, the data were deemed accurate and ready to be used. Figure 1 is the scatter plot that was used to determine that there were no outliers that needed to be removed from the weekly dining data.

Figure 1

Data Screening: Weekly dining interactions





Results for Null Hypothesis One

A simple linear regression was used to test if a student's average weekly dining interactions significantly predicted their GPA for their first and second semesters. A linear regression was used because the test assesses the relationship between two continuous variables. GPA and the students' average weekly dining interactions are continuous, with GPA serving as the dependent variable and dining data serving as the independent variable. A linear regression reveals whether the relationship between two variables is statically significant and how much of the variance of the dependent variable is explained by the independent variable (Cronk, 2018).

For the first semester data, a regression line was plotted to assess the linear relationship between dining interactions and GPA. Visual confirmation was used to determine that there was indeed a relationship between the variables. Upon running the linear regression, the prediction equation was: GPA = .049x + 2.43. A student's average weekly dining interactions statistically significantly predicted GPA, $F(1, 3055) = 96.002$, $p < 0.001$), accounting for 3% of the variance ($R^2 = .030$). See Table 5 for the ANOVA results.

Table 5
ANOVA 1

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	67.532	1	67.532	96.002	<.001[b]
	Residual	2149.038	3055	.703		
	Total	2216.571	3056			

a. Dependent Variable: GPA for first semester
b. Predictors: (Constant), Semester 1 Average Weekly Dining Interactions

For the second semester data, a regression line was used again to assess the linear relationship between dining interactions and GPA for the second semester. Visual confirmation determined that there was indeed a relationship between the variables. After running the linear regression, the prediction equation was: GPA = .059x + 2.348. A students average weekly dining interactions statistically significantly predicted GPA, $F(1, 2811) = 115.118$, $p < 0.001$), accounting for 3.9% of the variance ($R^2 = .039$). Table 6 displays the ANOVA results.

Table 6
ANOVA 2

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	87.084	1	87.084	115.188	<.001[b]
	Residual	2125.173	2811	.756		
	Total	2212.257	2812			

a. Dependent Variable: GPA for Second semester
b. Predictors: (Constant), Semester 2 Average Weekly Dining Interactions

After conducting each linear regression to test the null hypothesis, the researcher rejected the null hypothesis since both tests demonstrate that weekly dining interactions can statistically significantly predict GPA.

Results for Null Hypothesis Two

A binary logistic regression was used to evaluate the relationship between a student's average weekly dining interactions during their first semester and their persistence into their second semester. A logistic regression is different than a linear regression because a linear regression has two continuous variables, whereas a logistic regression accommodates a dichotomous variable and a continuous or categorical variable (Cronk, 2018). A logistic regression works to predict whether an observation falls into the dichotomous variable (Cronk, 2018). For these tests, the independent variable was the student's average weekly dining interactions and the dependent variable was whether the student enrolled in the next semester.

For the first semester data, the logistic regression model was statistically significant, χ^2 (1) = 40.143, $p < .001$. See Table 7 for the Omnibus Tests of Model Coefficients.

Table 7
Omnibus tests of model coefficients 1

		Chi-square	df	Sig.
Step 1	Step	40.143	1	<.001
	Block	40.143	1	<.001
	Model	40.143	1	<.001

The strength between dining interactions and student persistence was determined as weak by using the Nagelkerke R^2 (0.033), which means that the model explained 3.3% of the variance in persistence. Table 8 contains the Model Summary.

Table 8
Model summary 1

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1506.056[a]	.013	.033

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

The model using weekly dining interactions to predict persistence into the second semester was analyzed further using the Wald chi-squared test and odds ratios. The Wald chi-squared test was statistically significant, χ^2 (1) = 38.719, $p <0.001$. The odds ratios were examined to measure the result of each unit increase of the independent variable. Exp(B) was 1.165, which means the odds of persisting into the next semester increased by a factor of 1.16 for every additional dining interaction a student had. A summary of the Wald chi-squared statistics, odds ratios, and 95% confidence interval can be seen in Table 9.

Table 9
Variables in the equation 1

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1[a]	Semester 1 Average Weekly Dining Interactions	.153	.025	38.719	1	<.001	1.165	1.110	1.222
	Constant	1.290	.208	38.391	1	<.001	3.634		

a. Variable(s) entered on step 1: Semester 1 Average Weekly Dining Interactions.

Another binary logistic regression was used to evaluate the relationship between a student's average weekly dining interactions during their second semester and their persistence into their third semester. The logistic regression model was statistically significant, χ^2 (1) = 51.552, $p < .001$. See Table 10 for the Omnibus Tests of Model Coefficients.

Table 10
Omnibus tests of model coefficients 2

		Chi-square	df	Sig.
Step 1	Step	51.552	1	<.001
	Block	51.552	1	<.001
	Model	51.552	1	<.001

The strength between dining interactions and student persistence was determined as weak again by using the Nagelkerke R^2 (0.033), which means that the model explained 3.3% of the variance in persistence. Table 11 contains the Model Summary.

Table 11
Model summary 2

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	2213.755[a]	.018	.033

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

The model was further analyzed using the Wald chi-squared test and odds ratios. The Wald chi-squared test was statistically significant, $\chi^2 (1) = 49.882$, $p < 0.001$. The Exp(B), which indicates the odds ratios, was 1.142. This means that for every additional dining interaction a student had, the odds of them persisting into the third semester increased by a factor of 1.142. A summary of the Wald chi-squared statistics, odds ratios, and 95% confidence interval can be seen in Table 12.

Table 12
Variables in the equation 2

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B) Lower	Upper
Step 1[a]	Semester 2 Average Weekly Dining Interactions	.133	.019	49.882	1	<.001	1.142	1.101	1.185
	Constant	.653	.168	15.082	1	<.001	1.920		

a. Variable(s) entered on step 1: Semester 2 Average Weekly Dining Interactions.

After data analysis, the researcher can reject the null hypothesis since a student's average weekly dining interactions can predict whether they enroll in the next semester. While statistically significant, the relationship is weak.

Significant Change in Dining Habits Measurement

For the last two research questions, the students were grouped by whether they had experienced significant changes in their dining habits. Two levels of measurement were used based on the timing of major depressive disorder (MDD) symptoms, which must be present for more than 2 weeks. The first was whether a student changed their habit for at least 3 consecutive weeks based on a range determined by their standard deviation. The second was whether a student changed their habit for at least 2 weeks based on a dining habit range created using 1.5 of their standard deviation.

For the first semester data using the 1 SD range form of measurement, 571 out of the 3,112 students experienced changes in their dining habits. Using the 1.5 SD range, 249 students experienced a significant change in their dining habits. See Tables 13 and 14 for the percentage breakdown.

Table 13
Frequency Table 1

3 weeks in a row of change 1 SD S1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	2541	81.7	81.7	81.7
	1	571	18.3	18.3	100.0
	Total	3112	100.0	100.0	

Table 14
Frequency Table 2

2 weeks in a row of 1.5 SD change S1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	2862	92.0	92.0	92.0
	1	249	8.0	8.0	100.0
	Total	3111	100.0	100.0	
Missing	System	1	.0		
Total		3112	100.0		

For the second semester data, 465 out of the 3,112 students experienced changes in their dining habits suing the 1 SD range. Using the 1.5 SD range, 530 students from the sample experienced changes in their dining habits. See Tables 15 and 16 for the percentage breakdown.

Table 15
Frequency Table 3

3 weeks in a row of change 1 SD S2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	2647	85.1	85.1	85.1

	1	465	14.9	14.9	100.0
	Total	3112	100.0	100.0	

Table 16
Frequency Table 4

2 weeks in a row of 1.5 SD change S2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	2581	82.9	83.0	83.0
	1	530	17.0	17.0	100.0
	Total	3111	100.0	100.0	
Missing	System	1	.0		
Total		3112	100.0		

Both measurements were explored to assess whether they could predict academic success and retention.

Results for Null Hypothesis Three

A linear regression was used again to test null hypothesis three which evaluates the relationship between a student's GPA and their dining habits. A change in dining habits was the independent variable and the student's GPA was the dependent variable.

For the linear regression testing the relationship between GPA and a change in dining habits (3 consecutive weeks of change outside of the 1SD range), the prediction equation was: GPA = 2.913x + -.183. A change in dining habits statistically significantly predicted GPA, F(1, 3106) = 21.767, p <0.001. However, the habit change accounted for 0% of the variance (R^2 = .000). See Table 17 for the ANOVA results.

Table 17
ANOVA 3

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	15.558	1	15.558	21.767	<.001[b]

	Residual	2219.959	3106	.715		
	Total	2235.517	3107			

a. Dependent Variable: GPA for First semester
b. Predictors: (Constant), 3 weeks in a row of change 1 SD S1

Another linear regression was used to test the relationship between GPA and a change in dining habits measured by 2 consecutive weeks of change outside of the 1.5 standard deviation range. The prediction equation was: GPA = 2.900x + -.268. A change in dining habits statistically significantly predicted GPA, $F(1, 3105) = 23.067$, $p < 0.001$. Again, the habit change accounted for 0% of the variance ($R^2 = .000$). See Table 18 for the ANOVA results.

Table 18
ANOVA 4

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	16.480	1	16.480	23.067	<.001[b]
	Residual	2218.416	3105	.714		
	Total	2234.897	3106			

a. Dependent Variable: GPA for First semester
b. Predictors: (Constant), 2 weeks in a row of 1.5 SD change S1

Two more linear regressions were conducted using the data from the second semester. For the regression testing the relationship between GPA and a change in dining habits measured by 3 consecutive weeks of change outside of the 1 standard deviation range, the prediction equation was: GPA = 2.928x + -.252. A change in dining habits statistically significantly predicted GPA, $F(1, 2898) = 31.126$, $p < 0.001$. Again, the habit change accounted for 0% of the variance ($R^2 = .000$). See Table 19 for the ANOVA results.

Table 19
ANOVA 5

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24.857	1	24.857	31.126	<.001[b]
	Residual	2314.252	2898	.799		
	Total	2339.109	2899			

a. Dependent Variable: GPA for Second semester

b. Predictors: (Constant), 3 weeks in a row of change 1 SD S2

The regression testing the relationship between GPA and a change in dining habits measured by 2 consecutive weeks of change outside of the 1.5 standard deviation range, the prediction equation was: GPA = 2.910x + -.124. A change in dining habits statistically significantly predicted GPA, $F(1, 2897) = 8.251$, $p = 0.004$. Again, the habit change accounted for 0% of the variance. See Table 20 for the ANOVA results.

Table 20
ANOVA 6

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.642	1	6.642	8.251	.004[b]
	Residual	2332.215	2897	.805		
	Total	2338.858	2898			

a. Dependent Variable: GPA for Second semester
b. Predictors: (Constant), 2 weeks in a row of 1.5 SD change S2

Upon reviewing the results from the linear regressions, the researcher rejected the null hypothesis since changes in dining habits seem to predict GPA, however, the change in dining habits do not contribute to the variance.

Results for Null Hypothesis Four

Chi-square tests of independence were used to assess the relationship a change in dining habits has on whether a student returns for the next semester. The variables used for null hypothesis four are categorical resulting in a 2 x 2 chi-square analysis. A student either changed their habit or they did not and they either enrolled in the next semester or they did not. Chi-square tests look at the expected outcome and the observed outcome and whether there is a difference between the two (Cronk, 2018).

For the first semester data, a chi-square test was run when the habit changes were measured by 3 consecutive weeks of change using a range based on 1 standard deviation. The test measured the expected and observed outcomes of students who did or did not enroll in their second semester. All expected cell frequencies were greater than five. There was a statistically significant association between a change in dining habits and persistence into the next semester, $\chi^2(1) = 11.756$, $p < 0.001$. See Table 21 for the chi-square results.

Table 21
Chi-square tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	11.756[a]	1	<.001		
Continuity Correction[b]	11.137	1	<.001		
Likelihood Ratio	10.683	1	.001		
Fisher's Exact Test				<.001	<.001
N of Valid Cases	3112				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 39.27.
b. Computed only for a 2x2 table

The observed number of students that did not enroll in the next semester was 214. The model expected 39.3 of those students to have experienced a change in dining habit. However, 58 students were observed to have changed their dining habit. This is an increase of 19 students from the constant model to the model that included dining data.

Also, since 58 students experienced a change in their dining habit, that accounts for 27.1% of those that did not return. In other words, 1 in 4 students that did not return experienced a change in their dining habits. See Table 22 for the crosstabulation results.

Table 22
Crosstabulation 1

		3 weeks in a row of change 1 SD		
		N	Y	Total
N	Count	156	58	214
	Expected Count	174.7	39.3	214.0

Started second semester		% within Started second semester	72.9%	27.1%	100.0%
		% within 3 weeks in a row of change 1 SD S1	6.1%	10.2%	6.9%
		% of Total	5.0%	1.9%	6.9%
	Y	Count	2385	513	2898
		Expected Count	2366.3	531.7	2898.0
		% within Started second semester	82.3%	17.7%	100.0%
		% within 3 weeks in a row of change 1 SD S1	93.9%	89.8%	93.1%
		% of Total	76.6%	16.5%	93.1%
Total		Count	2541	571	3112
		Expected Count	2541.0	571.0	3112.0
		% within Started second semester	81.7%	18.3%	100.0%
		% within 3 weeks in a row of change 1 SD S1	100.0%	100.0 %	100.0%
		% of Total	81.7%	18.3%	100.0%

Another chi-square test was conducted when the habit changes were measured using 2 consecutive weeks of changes using a range based on 1.5 standard deviation. All expected cell frequencies were greater than five. There was a statistically significant association between a change in dining habits and persistence into the next semester, $\chi^2(1) = 13.114$, $p < 0.001$. See Table 23 for the chi-square results.

Table 23
Chi-square tests 2

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	13.114[a]	1	<.001		
Continuity Correction[b]	12.186	1	<.001		
Likelihood Ratio	10.959	1	<.001		
Fisher's Exact Test				<.001	<.001
N of Valid Cases	3111				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 17.13.
b. Computed only for a 2x2 table

The observed number of students that did not enroll in the next semester was 214. The constant model predicted that 17 students would have changed their dining habits. The observed number of those that did not enroll in the next semester but did experience a change in their dining habit was 31. The model including dining data increased the observed by 14 students. Almost 3 of every 20 students that did not enroll in the next semester experienced a change in their dining habits. See Table 24 for the crosstabulation results.

Table 24
Crosstabulation 2

			2 weeks in a row of 1.5 SD change		
			N	Y	Total
Started second semester	N	Count	183	31	214
		Expected Count	196.9	17.1	214.0
		% within Started second semester	85.5%	14.5%	100.0%
		% within 2 weeks in a row of 1.5 SD change S1	6.4%	12.4%	6.9%
		% of Total	5.9%	1.0%	6.9%
	Y	Count	2679	218	2897
		Expected Count	2665.1	231.9	2897.0
		% within Started second semester	92.5%	7.5%	100.0%
		% within 2 weeks in a row of 1.5 SD change S1	93.6%	87.6%	93.1%
		% of Total	86.1%	7.0%	93.1%
Total		Count	2862	249	3111
		Expected Count	2862.0	249.0	3111.0
		% within Started second semester	92.0%	8.0%	100.0%
		% within 2 weeks in a row of 1.5 SD change S1	100.0%	100.0%	100.0%
		% of Total	92.0%	8.0%	100.0%

In analyzing the second semester data for null hypothesis four, more chi-square tests were conducted on whether students enrolled in their first semester. Students that left the institution or did not have a meal plan their second semester were removed from these tests. Because of this 2,808 students were included in the following chi-square tests.

The first test measured habit changes using 3 consecutive weeks of changes using a range based on 1 standard deviation. All expected cell frequencies were greater than five. There was a statistically significant association between a change in dining habits and persistence into the next semester, χ^2 (1) = 27.210, $p < 0.001$. See Table 25 for the chi-square results.

Table 25
Chi-square tests 3

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	27.210[a]	1	<.001		
Continuity Correction[b]	26.445	1	<.001		
Likelihood Ratio	24.587	1	<.001		
Fisher's Exact Test				<.001	<.001
N of Valid Cases	2808				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 63.67.
b. Computed only for a 2x2 table

The observed number of students that did not enroll in the next semester was 387. The constant model expected 63.7 of the 387 students to experience a change in their dining habits. However, the observed students who changed their dining habits was 99. The model including dining data increased the observed students by 37. Also, 1 in every 4 students that did not enroll in the next course experienced a change in their dining habit. See Table 26 for the crosstabulation results.

Table 26
Crosstabulation 3

			3 weeks in a row of change 1 SD		
			N	Y	Total
Started third semester	N	Count	288	99	387
		Expected Count	323.3	63.7	387.0
		% within Started third semester	74.4%	25.6%	100.0%
		% within 3 weeks in a row of change 1 SD S2	12.3%	21.4%	13.8%
		% of Total	10.3%	3.5%	13.8%
	Y	Count	2058	363	2421
		Expected Count	2022.7	398.3	2421.0
		% within Started third semester	85.0%	15.0%	100.0%
		% within 3 weeks in a row of change 1 SD S2	87.7%	78.6%	86.2%
		% of Total	73.3%	12.9%	86.2%
Total		Count	2346	462	2808
		Expected Count	2346.0	462.0	2808.0
		% within Started third semester	83.5%	16.5%	100.0%
		% within 3 weeks in a row of change 1 SD S2	100.0%	100.0%	100.0%
		% of Total	83.5%	16.5%	100.0%

Another chi-square test was run when the habit changes were measured using two consecutive weeks of changes using a range based on 1.5 standard deviation. All expected cell frequencies were greater than five. There was a statistically significant association between a change in dining habits and persistence into the next semester, χ^2 (1) = 7.914, p = 0.005. See Table 27 for the chi-square results.

Table 27
Chi-square tests 4

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	7.914[a]	1	.005		

Continuity Correction[b]	7.525	1	.006		
Likelihood Ratio	7.506	1	.006		
Fisher's Exact Test				.006	.004
N of Valid Cases	2808				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 72.91.
b. Computed only for a 2x2 table

The observed number of students that did not enroll in the next semester was 387. The constant model expected 72.9 of the 387 students to have experienced a change in their dining habit. However, 93 students who did not enroll in the next semester experienced a change in dining habits. Including dining data in the model increased the observed by 20 students. See Table 28 for the crosstabulation results.

Table 28
Crosstabulations 4

			2 weeks in a row of 1.5 SD change		
			N	Y	Total
Started third semester	N	Count	294	93	387
		Expected Count	314.1	72.9	387.0
		% within Started third semester	76.0%	24.0%	100.0%
		% within 2 weeks in a row of 1.5 SD change S2	12.9%	17.6%	13.8%
		% of Total	10.5%	3.3%	13.8%
	Y	Count	1985	436	2421
		Expected Count	1964.9	456.1	2421.0
		% within Started third semester	82.0%	18.0%	100.0%
		% within 2 weeks in a row of 1.5 SD change S2	87.1%	82.4%	86.2%
		% of Total	70.7%	15.5%	86.2%
Total		Count	2279	529	2808
		Expected Count	2279.0	529.0	2808.0
		% within Started third semester	81.2%	18.8%	100.0%

	% within 2 weeks in a row of 1.5 SD change S2	100.0%	100.0%	100.0%
	% of Total	81.2%	18.8%	100.0%

Using the chi-square tests, the researcher can reject the null hypothesis since a change in dining habits statistically significantly predicts whether a student will enroll in the next semester. These results are the most significant of the study.

Summary

Based on the results of the linear regressions, binary logistic regressions, and the chi-square tests, it is evident that there is a relationship between dining interactions and academic success and persistence. Key findings are bulleted below, with the most significant finding listed first.

- Of the students that left the institution during the study, anywhere from 14.5% to 27% of them had a significant change in dining habits for at least 2 consecutive weeks.
- Students that left the institution interacted with dining services less than their peers that stayed.
- Weekly dining interactions can predict GPA but do not account for much of the variance of GPA.
- For every additional dining interaction a student had each week, they were between 114% and 116% as likely to enroll in the next semester.
- Adding dining data to the models that predict persistence in the next semester increased the accuracy of the model's predictive power.

CHAPTER FIVE

CONCLUSIONS

Overview

Students leave college after starting for a variety of reasons and since Vincent Tinto published his first framework in 1975, higher education leaders have been conducting research on retention all over the world. This research assists institutions as they support students physically, emotionally, and mentally to lower drop-out rates. Financial hardship, mental health, and academic difficulty are just a few reasons students leave institutions. (Boyd et al., 2020; Kang et al., 2018; Sokratous et al., 2013; van Rooij et al., 2018).

As the information technology field widens, so does the use of data in retention efforts. The literature is clear that certain data points, like high school GPA, high stakes test scores, and academic engagement, help institutions personalize support for students who may need it (Cui at el., 2019; De Clerq et al., 2018; Saunders-Scott et al., 2018).

It is also clear that a student's first year at the institution is important. Students are leaving college at high rates after completing their first year (De Clercq et al., 2018). Not all students adjust well to the academic rigor and newfound freedom in college. Students may experience increased stress levels and even depression, which can impact their daily functions (Dusselier et al., 2005; Hysenbegasi et al., 2005; Sokratous et al., 2013). Data from the American College Health Association also indicated that since 2011, college students have had increased levels of hopelessness, depression, and anxiety (American College Health Association, 2021, 2019, 2015, 2011).

What is lacking in current literature surrounding retention and academic success is the use of proven predictors that are collected and analyzed in real to near-real time that give insight in the mental and physical wellness of students during the semester. This causal-correlational study sought to solve that problem by assessing whether dining data in the form of weekly interactions could be used to predict academic success and retention. This chapter will conclude this study by discussing the results, the implications based on the results, the limitations of the study as well as what future research on the topic could cover.

Discussion

To assess the relationship between dining data and retention and academic success, de-identified archival data was used. This study included 3,112 students who enrolled at the institution during the falls of 2016, 2017, and 2018 who met the qualifications for the study. All 3,112 students were new with zero transfer credits who lived on campus and had a meal plan. The meal plan allowed for students to buy food from the main dining hall as well as other retail food locations on campus.

The dining data collected and used as the independent variable only included interactions that occurred on Monday through Friday for the students' first two semesters. The students' semester GPAs and course enrollment into their first three semesters were used as the dependent variables. The tests and the results are detailed below.

Research Question One

Research question one assessed the relationship between the student's average weekly dining interactions and their GPA. A linear regression was used since both variables were continuous. The relationship between dining interactions and GPA was statistically significant ($p < 0.001$, $p < 0.001$), however, the interactions did not account for much of the variance. This means that while dining data may predict GPA, about 97% of the students' GPA can be attributed to other factors. As seen in the literature, socioeconomic status, academic skills, motivation, language efficiency, physical and mental well-being, and class attendance are examples of confirmed predictors of GPA and academic success (Bauman et al., 2019; Coetzee, 2011; De Clercq et al., 2018; Burger & Naude, 2020; Li et al., 2010).

To assess the relationship between average weekly dining interactions and GPA when other variables are included, more linear regressions were conducted. The model analyzing the first semester data that included dining data, high school GPA, and the amount of credit hours the student earned for the semester, was statistically significant $F(3, 2985) = 446.507$, $p < .0001$ accounting for 31% of the variance ($R^2 = .310$). See Tables 29 and 30 for the ANOVA values and the coefficients. The prediction equation for GPA was: GPA= -.466 + (.761 x HS GPA) + (.040 x earned credit hours) + (.025 x average weekly dining interactions).

Table 29
ANOVA 7

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	601.438	3	200.479	446.507	<.001[b]
	Residual	1340.251	2985	.449		
	Total	1941.689	2988			

a. Dependent Variable: GPA for First semester

b. Predictors: (Constant), Semester 1 Average Weekly Dining Interactions, Earned Credit Hours for first semester, HS_GPA

Table 30
Coefficients 1

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.466	.099		-4.722	<.001
	HS_GPA	.761	.028	.415	26.779	<.001
	Earned Credit Hours for first semester	.040	.002	.281	18.245	<.001
	Semester 1 Average Weekly Dining Interactions	.025	.004	.095	6.171	<.001

a. Dependent Variable: GPA for First semester

The model analyzing the second semester data that included dining data, high school GPA, and the amount of credit hours the student earned for the semester, was statistically significant F(3, 2724) = 457.484, p < .0001 accounting for 33.5% of the variance (R^2 = .335). See Tables 31 and 32 for the ANOVA values and the coefficients. The prediction equation for GPA was: GPA= -.546 + (.761 x HS GPA) + (.045 x earned credit hours) + (.024 x average weekly dining interactions).

Table 31
ANOVA 8

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	594.507	3	198.169	457.484	<.001[b]
	Residual	1179.958	2724	.433		
	Total	1774.464	2727			

a. Dependent Variable: LU GPA for Second semester

b. Predictors: (Constant), Semester 2 Average Weekly Dining Interactions, Earned Credit Hours for second, HS_GPA

Table 32
Coefficients 2

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.546	.103		-5.277	<.001
	HS_GPA	.761	.030	.410	25.797	<.001
	Earned Credit Hours for second	.045	.002	.326	20.590	<.001
	Semester 2 Average Weekly Dining Interactions	.024	.004	.088	5.586	<.001

a. Dependent Variable: GPA for Second semester

The results of these two additional linear regressions indicate that not only are average weekly dining interactions a confirmed predictor of academic success, when added to models that include other variables, it contributes to the statistical significance of the model.

Research Question Two

Binary logistic regressions were conducted to assess the relationship between the students' average weekly dining interactions and their persistence into the next semester. Both tests that assessed first and second semester data resulted in a statistically significant relationship ($p < 0.001$, $p < 0.001$). The odds ratio was helpful in determining the impact the dining interactions had on persistence. For every additional interaction during the week, the likelihood of the student enrolling in the next semester increased by a factor of 1.16 for the first semester data and 1.14 for the second semester data. This indicates that for every additional interaction, students were more likely than not to enroll in the next term than to not come back to the institution.

As seen in Table 3, students that did not persist to the next semester had lower average weekly dining interactions. Students that did not enroll in the second semester ($M = 7.875$) had on average 1.34 less interactions than their peers that came back ($M = 9.224$). Students that did not enroll in their third semester ($M = 8.245$) had on average 1.16 less interactions than their peers that came back ($M = 9.411$).

Habit Change Measurements

Research questions three and four used changes in dining habits as the independent variable with GPA and persistence into the next semester as dependent variables. The changes in dining habits were determined by the researcher using the students' average weekly interactions and standard deviations. A range was created for each student using 1 standard deviation above and below their weekly average. Another range was created using 1.5 standard deviations above and below the students' weekly average. If the students' weekly dining interactions did not fall in the ranges determined as their normal dining habits, it was determined to be a habit change. Three consecutive weeks outside of the 1 standard deviation range resulted in 465 students with changes in their habits. Two consecutive weeks outside of the 1.5 standard deviation range resulted in 530 students who experienced changes in their dining habits. These measurements were used in the tests detailed below.

Research Question Three

Research question three was assessed using a linear regression with changes in dining habits and GPA. Like research question two, the tests were statistically significant ($p < 0.001$, $p < 0.001$) indicating an important relationship between habit changes in GPA, however, habit changes accounted for an even smaller amount of the variance (<1%).

To explore whether changes in dining habits remains a predictor when other variables are included in the model, more linear regressions were conducted. Using the first semester data, both models analyzing the changes in dining habits were statistically significant $F(3, 3034) = 519.630$, $p < .0001$ accounting for 30.2% of the variance ($R^2 = .302$) and $F(3, 3033) = 519.567$, $p < .0001$ accounting for 30.2% of the variance ($R^2 = .302$). The prediction equations for GPA were: GPA= -.255 + (.773 x HS GPA) + (.041 x earned credit hours) - (.107 x changes in habits) and GPA= -.269 + (.775 x HS GPA) + (.041 x earned credit hours) - (.159 x changes in habits). See Tables 33 through 36 for the ANOVA results and the coefficients.

Table 33
ANOVA 9

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	591.630	3	197.210	437.541	<.001[b]
	Residual	1367.495	3034	.451		

	Total	1959.125	3037			

a. Dependent Variable: GPA for First semester

b. Predictors: (Constant), 3 weeks in a row of change 1 SD S1, Earned Credit Hours for first semester, HS_GPA

Table 34
Coefficients 3

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.255	.096		-2.665	.008
	HS_GPA	.773	.028	.423	27.489	<.001
	Earned Credit Hours for first semester	.041	.002	.283	18.415	<.001
	3 weeks in a row of change 1 SD S1	-.107	.032	-.052	-3.395	<.001

a. Dependent Variable: GPA for First semester

Table 35
ANOVA 10

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	591.567	3	197.189	437.516	<.001[b]
	Residual	1366.975	3033	.451		
	Total	1958.542	3036			

a. Dependent Variable: GPA for First semester

b. Predictors: (Constant), 2 weeks in a row of 1.5 SD change S1, HS_GPA, Earned Credit Hours for first semester

Table 36
Coefficients 4

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.269	.095		-2.828	.005
	HS_GPA	.775	.028	.424	27.593	<.001
	Earned Credit Hours for first semester	.041	.002	.283	18.399	<.001

	2 weeks in a row of 1.5 SD change S1	-.159	.045	-.053	-3.517	<.001

a. Dependent Variable: GPA for First semester

Using the second semester data, both models analyzing the changes in dining habits were statistically significant F(3, 2797) = 594.493, $p < .0001$ accounting for 32.9% of the variance (R^2 = .329) and F(3, 2796) = 589.045, $p < .0001$ accounting for 32.6% of the variance (R^2 = .326). The prediction equations for GPA were: GPA= -.346 + (.775 x HS GPA) + (.045 x earned credit hours) - (.130 x changes in habits) and GPA= -.364 + (.777 x HS GPA) + (.045 x earned credit hours). Note that changes in dining data was not a contributing variable and was not included in the prediction equation. See Tables 37 through 40 for the ANOVA results and the coefficients.

Table 37
ANOVA 11

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	594.493	3	198.164	457.592	<.001[b]
	Residual	1211.267	2797	.433		
	Total	1805.761	2800			

a. Dependent Variable: GPA for Second semester

b. Predictors: (Constant), 3 weeks in a row of change 1 SD S2, HS_GPA, Earned Credit Hours for second

Table 38
Coefficients 5

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-.346	.099		-3.498	<.001
	HS_GPA	.775	.029	.420	26.765	<.001
	Earned Credit Hours for second	.045	.002	.326	20.764	<.001
	3 weeks in a row of change 1 SD S2	-.130	.034	-.059	-3.798	<.001

a. Dependent Variable: GPA for Second semester

Table 39
ANOVA 12

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	589.045	3	196.348	451.280	<.001[b]
	Residual	1216.519	2796	.435		
	Total	1805.564	2799			

a. Dependent Variable: GPA for Second semester

b. Predictors: (Constant), 2 weeks in a row of 1.5 SD change S2, HS_GPA, Earned Credit Hours for second

Table 40
Coefficients 6

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.364	.099		-3.674	<.001
	HS_GPA	.777	.029	.420	26.752	<.001
	Earned Credit Hours for second	.045	.002	.326	20.770	<.001
	2 weeks in a row of 1.5 SD change S2	-.049	.032	-.023	-1.506	.132

a. Dependent Variable: GPA for Second semester

Research Question Four

The relationship between habit change and persistence into the next semester was explored using chi-square tests for research question four. The chi-square tests looked at the expected outcomes and the observed outcomes to see if there was a difference. The results indicated that a change in dining habit, whether for 3 consecutive weeks outside of the 1 standard deviation range or 2 consecutive weeks outside of the 1.5 standard deviation range, did statistically significantly predict persistence ($p < 0.001$, $p < 0.001$, $p < 0.001$, $p = 0.005$).

Not only is the relationship between changes in dining habit and persistence statistically significant, but the models including changes in dining habit greatly increased the accuracy of the predictive model. The number of students that experienced a habit change and did not persist to the next semester was higher than the expected outcome for each test. Additionally, almost 28% of students that did not persist had a habit change during their last semester enrolled using one of the measurements.

Most Significant Findings

While all null hypotheses were rejected, the findings from research questions four were the most significant findings of this study. When the chi-square tests were conducted, the models that included significant changes in dining habits were significantly different that the expected models when the sample was equally distributed. For every additional student found in the model, the model became more and more accurate. Also, the fact that 27% of the students that left the institution experienced changes in their dining habits is important to note. That means that for every four students that left the institution, at least one of them experienced changes in their dining habits.

Dining Data as a Predictor

The results of this study contribute to literature by confirming that dining data is a predictor of academic success and retention. This means dining data should be considered when institutions use data to support retention initiatives.

Research questions one and three explored whether dining data can predict academic success. The dining data used for research question one were the students' average weekly dining interactions. The dining data used for research question three were whether the student experience changes in their dining habits. Both null hypotheses were rejected since dining data predicted some variance of GPA based on the sample. While the dining data did not account for a large portion of the variance, when other variables were controlled for, dining data still found unique variance of GPA and made the models more accurate. This is important to note since it confirms that dining data should be used in addition to other proven predictors when analyzing GPA.

Research questions two and four explored whether dining data can predict retention and persistence into the next term. The dining data used for research question two were the students' average weekly dining interactions while the dining data used for research question four were whether the students experienced changes in their dining habits. Both null hypotheses were rejected since the tests confirmed that dining data predicted retention.

Research question two indicated that for every additional interaction a student has with dining services, students were between 114% and 116% as likely to enroll in the next semester (Exp(B) = 1.142, Exp(B) = 1.165). This means that for every additional dining interaction, the student was more likely than not to enroll in the next semester.

Research question four revealed that adding dining data to the predicting model increased the accuracy of the model. The difference between the model without dining data and the model with dining data was statistically significant ($p < 0.001$, $p < 0.001$, $p < 0.001$, $p = 0.005$). For every additional student found in the observed group of students that did not enroll and experienced changes in their dining habit than the expected group, the model become more and more accurate. The model with dining data found between 20 and 37 additional students, which indicates that including dining data greatly increased the accuracy of the model. These tests also confirm that dining data can predict retention and should be added to use by institutions in their data analytics.

Dining Data as a Proxy for Wellness

Research shows that institutions should prioritize their support of students' physical wellness and mental health (Benson-Tilsen & Cheskis-Gold, 2017). The habits students establish in college likely affect their behavior after college (El Ansari et al., 2015; Upcraft & Gardner, 1989). Based on data from the American College Health Association, college students' mental health has been declining over the last 10 years (American College Health Association, 2021, 2019, 2015, 2011). Results from surveys revealed that over the last ten years, students have felt increasingly lonely, hopeless, depression, and anxiety (American College Health Association, 2021, 2019, 2015, 2011). There is no doubt that these feelings impact students' daily lives and academic success.

The challenges faced while in college can contribute to stress, anxiety, and depression (Dusselier et al., 2005). When students experience stress, anxiety, and/or depression, they will likely experience sleep disturbances, headaches, and changes in appetite. These symptoms can harm students' academic performance and eating habits (Dusselier et al., 2005; Saunders-Scott et al., 2018; Sogari et al., 2018).

Currently, institutions can only gather data on students' physical and mental wellness through surveys students fill out. This is problematic because it is up to the student to disclose pertinent information. More research must be done to solidify this thought, but since stress, anxiety, and other difficult life experiences lead to a change in eating habits or skipping of meals, dining data could be used to measure physical and emotional wellness. This study used dining data that can be collected and analyzed in real or near-real time that may serve as a theoretical proxy for physical and mental wellness.

Connection to the First-year Experience

It is well known that the transition from high school to college can be difficult. Out of the students that leave institutions, many of them leave after their first year (Purdie & Rosser, 2011). Some students find that managing their time is difficult. Others find that the academic rigor of college is more than they expected. Students may also have a difficult time managing their newfound freedom and social life. Other students may neglect their physical and emotional wellbeing. All these factors and more can cause stress and depression. Stress and depression can in turn cause a change in dining habits, whether it is binge eating/drinking or a loss of appetite (Ivezaj et al., 2010; Finch & Tomiyama, 2015). Previous studies show that students who experience depression struggle academically. (Hysenbegasi et al., 2005; Sokratous et al., 2013).

The results of this study confirmed a clear connection between dining interactions and academic success and retention in first-year students. The more interactions a student has with dining services on a weekly basis increases the likelihood of them succeeding academically and enrolling in the next semester. Similarly, students that do not experience changes in their dining habits tend to have a higher GPA and are more likely to enroll in the next semester. These results were expected given the existing research. This study contributes to the existing literature about retention and academic success in higher education as well as the literature about physical wellness and mental health in first-year students.

For this reason, institutions should investigate how they can add dining data to existing data collection and analysis. Integrating dining data will help institutions find students that may need assistance.

Implications

Integrating Dining Data into Data Analysis

The results from all four research questions should not be ignored. Questions one and three confirm a statistically significant relationship between dining data and academic success/GPA in first-year students. Dining data found unique variance in GPA when added to models with other predictors. Questions two and four confirm a statistically significant relationship between dining data and retention. Question four confirmed that almost 28% of the students that left the institution experienced changes in their dining habits using one of the measurements. Adding dining data to the models increased the predictive ability and accuracy of the models.

In light of these results, dining data should be added to current predictive analytics if institutions wish to identify struggling students. Based on the results of research question four, integrating changes in dining habits in data collect and analysis geared towards predicting student persistence should be prioritized since it was the most significant finding.

Education data mining (EDM) is when data is analyzed through established and automatic algorithms (Baker & Inventado, 2014). Predictive analytics and regressions are commonly used forms of EDM (Baker & Inventado, 2014). While Learning Analytics (LA) are used by students and faculty to evaluate learning in real time, Academic Analytics (AA) are used by administrators on a larger and mostly school-wide scale (Baker & Inventado, 2014; Nguyen et al., 2020). Predictive analytics use trends from past data to assess current data in an effort to predict an outcome (Daniel, 2015). The implications for this study involve EDM, AA and predictive analytics.

Currently, AA includes data points like high school GPA, class attendance, FAFSA submission date, missing assignments, test scores, and more (Cui at el., 2019; Herodotou, et al., 2019). These data points are commonly used because they are easily accessible and can automatically feed into certain analytics and dashboards. Some of the data is available throughout the semester, while others are only available after final grades are posted. All these data points have been proven to predict academic success and persistence, but most of the data points are assessing academic data. There is a gap in research that uses real or near-real time data that is accessible throughout the semester that may inform as to how students' physical and emotional wellness are.

However, now that a relationship between dining data and academic success and persistence has been established, dining data collected in real or near-real time can be added to predictive analytics that would, in real time, identify students that have low dining interactions or changed their habits. One study on the use of dining data to establish social connections found that students' dining habits were solidified within the first eight or nine days of the semester (Patel, 2019). This indicates that within 2 or 3 weeks into the semester, predictive analytics could be used to identify students that may have low dining interactions or have changed their dining habits. After identifying the students, nudges could be used to connect with them.

Using Dining Data for Nudges

Nudges are fairly new in higher education and are often texts, emails, or personalized interactions that are in response to predictive analytics (Blumenstein, 2018). Nudges usually call students to some sort of action, like submit a missing assignment or attend a tutoring session (Blumenstein, 2018). If nudges are implemented based off predictive analytics using dining data, a variety of call to actions could be put in place.

First, the student could receive an automatic email from their academic advisor asking how their semester is going. The email could also include a one-question survey the student fills out indicating how they feel. It could also produce an email from the student's dean encouraging them to visit academic support services or student counseling services if they ever needed something. The student does not have to know why they are being emailed, but these types of nudges give the student an opportunity to connect with an institutional service that can assist them.

Second, a series of texts could be sent over several weeks that offer physical and mental wellness tips, such as the importance of eating breakfast or how a walk outside can help clear their mind. These informational nudges, while they do not call students to a specific measurable action, can still remind students that the institution cares for them while supplying them with advice that would likely help them.

Also, based on how the nudges are sent, data can be collected and analyzed from the nudges. For example, if a nudge is sent to the student with an email from their advisor with a survey in it, data can be collected from the survey. It would be good to know if the student received the email and then completed the survey. They completed their call to action, which can in turn lead to more data be collected and analyzed that will ultimately help the student. If the email went out and the student did not respond, that may lead to another type of nudge, like a text from their advisor or a phone call.

Personalizing Dining Data for Use

While this study used dining data in two forms, which have now been confirmed as predictors of academic success and retention, institutions should do their own research on how their data can best be used. This research should include what the institution can collect, when the data is updated, where and how it is stored, and whether it can predict retention and academic success at that institution. If an institution has access to and can collect daily habits, those could be used instead of the weekly habits used in this study. If the institution collects the type of food purchased, then the dining data could be coded into different food categories and assessed. If the institution has access to and can collect how long a student stays in the cafeteria, the dining data could include the length of time spent with access to food.

It is imperative that institutions continually analyze what data they use, how the data best describes their students, and what they will do with the data once it is collected.

Limitations

Several limitations have been identified by the researcher. First, while dining data can be collected automatically, the data may not always be that of the assumed student. At the research institution, dining data is pulled from student swipes. A student's school ID card is used to purchase food; however, it cannot always be verified that it is the student using the ID. A student could very well give their ID card to a friend to use who may live off campus or who lost their own ID. Unless an institution checks the students' ID every time they interact with dining services, it is possible that the data is not reflective of the students' actual interactions and habits.

Another limitation to this study is that it did not account for the type of meal plan students purchased. During the semesters evaluated, there were two different types of meal plans. While both meal plans offered the same number of meals, one meal plan included access to the dining hall and limited access to retail locations on campus. The other meal plan was more expensive and gave students access to the dining hall and food at all the retail locations. For example, a student with the basic meal plan would be able to get a coffee at the on-campus coffee shop, however, the student with the more expensive plan could get coffee and a muffin at the coffee shop.

This study also only assessed the number of times a student interacted with dining services and not what the student purchased when, which is another limitation. Research shows that healthy eating is imperative for brain functions that support learning and academic success (Brandley et al., 2020; Moosman, 2017). Research also reveals the importance of eating breakfast (Kang et al., 2018). Since the study did not evaluate what the student ate and when, conclusions cannot be drawn about the physical benefits of each interaction. One student could have consumed cheese pizza at all interactions while another had well balanced meals and this study did not take that into consideration.

Lastly, this study did not evaluate in depth how a student's housing location may impact their dining habits. For example, some housing on campus has a kitchen where students can make their own food or store purchased food in a standard-size refrigerator. Also, the research campus is also fairly large with some housing located very close to the dining hall and very far from the dining hall. For these reasons, not controlling for the type of housing assignment and the distance the students are from the main eating areas is a limitation.

Recommendations for Further Study

Further research on how dining data can help support academic success and retention should be considered. While this study established a new connection between dining data and academic success and retention, it should be duplicated to solidify the generalizability of the connection at other institutions. Replications of this study should be done at a variety of institutions, like large state schools and small private schools.

Another suggestion is to control for or break down dining interactions and habits based on housing assignments. Campuses across the country offer a variety of housing options for students and so this aspect of campus life and its impact on dining habits should be investigated.

Additionally, when investigating changes in dining habits, more research should be conducted that evaluates when students change their dining habits. This study included any two or three consecutive week block of a dining habit change but evaluating whether changes happen at certain points of the semester could increase our understanding of what may cause the change in dining habits.

Also, this study only included dining interactions that occurred between Monday and Friday. Further research should be conducted that includes dining interactions that occur on the weekends.

Lastly, after implementing predictive analytics to identify students with low dining interactions or a change in dining habits, qualitative research should be conducted to help understand the student's lived experiences.

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APPENDIX I: Data Access Approval

Manicone, Hailey Anne [redacted]

From: [redacted]

Sent: Tuesday, October 26, 2021 9:24 AM

To: Manicone, Hailey Anne [redacted]

Subject: RE: Data Permission & Approval for Dissertation

I am fine with this Hailey. Reach out to me any time if you have some specific questions that I can help you with relatedto this project.

[redacted]

Vice President Auxiliary Services

From: Manicone, Hailey Anne [redacted]
Sent: Thursday, October 21, 2021 12:30 PM
To: [redacted]
Subject: Data Permission & Approval for Dissertation

Good afternoon, [redacted]!

While I am a full-time staff member at [redacted] in [redacted] I amcurrently pursing my Ed.D. at the University of Lynchburg.

My dissertation title is "The Use of Dining Data to Increase Retention and Academic Success in Residential First-Year Students." I hope to investigate the relationship weekly dining interactions might have with academic success and retention. I aim to do just that by using de-identified archival data from the fall of 2016 through the spring of 2019. This data will include the number of weekly dining interactions for brand new on-campus students, as well as, their high school GPA, [redacted] GPA for first their first three semesters, gender, ethnicity, number of credit hours for their first three semesters, and housing assignment for their first two years.

Therefore, I am emailing you to seek permission and approval for access and use of the data points above in order toconduct my quantitative study. Upon reviewing the data and completion of my dissertation, I hope to contribute to current literature that exists about how universities use dining data to support student success.

Thank you for reviewing this with me! Please let me know if you have any questions!

-Hailey Manicone

APPENDIX II: IRB Exemption Letter

University of Lynchburg Institutional Review Board for Human Subjects Research
Research Determination Letter

Date: November 4, 2021
To: Dr. Todd Olsen
From: Institutional Review Board (IRB)
Review Reference No.: LHS2122058
Project Title: The Use of Dining Data to Increase Retention and Academic Success in Residential First-Year Students
Final Determination: Not Human Subjects Research
Date of Determination: November 4, 2021

This letter serves to inform you that the details of the aforementioned project/activity that was submitted for IRB reviewability have been carefully considered. It has been determined that the project/activity does NOT require IRB oversight or approval. The study is classified as "non-reviewable, non-human subjects research" and has been assigned an identification number (see above).

The project/activity does not meet the definition of research as outlined in 45 CFR 46.102(d). This regulation defines research as a systematic investigation, including research development, testing and evaluation, designed to develop of contribute to generalizable knowledge and using human subjects. While the intent of your project/activity may be to contribute to the generalizable knowledge in your area of study and there are aspects of the project/activity that might involve or impact humans, the activity does not meet the federal government definitions for human subjects involvement that would necessitate IRB oversight.

This letter conveys that IRB oversight and approval of this project/activity is not necessary, however, this letter does not grant institutional approval. If your project/activity involves items that fall under the permission purview or authority of other entities, then separate arrangements may need to be made. Please avoid referring to your project as "human subjects research" in any project-related dissemination (oral, visual, or written) because this reference would contradict the IRB's determination of the project's/activity's status and might lead to further regulatory oversight.

We appreciate the opportunity to review your project/activity. Please notify the IRB Director if the scope or purpose of the study changes. On behalf of the Lynchburg IRB, I wish you the very best with your scholarship activity.