THE EFFECTS OF INTERNET ADDICTION ON COLLEGE STUDENTS: THE RELATIONSHIP BETWEEN INTERNET ADDICTION TEST SCORES, COLLEGE STUDENT DEMOGRAPHICS, AND ACADEMIC ACHIEVEMENT

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Submitted to the Faculty of the
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in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
December, 2019

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ACKNOWLEGMENTS

One of my top strengths on the Gallup Strengths Finder is Individualization. It is difficult for a person with this strength to make blanket compliments or give the same gift to everyone on a team. Because of this, my acknowledgements section is going to be specific. Each person along this journey is special to me in different ways, and I hope this section provides a small glimpse of the gift each of you are in my life. As Julie Andrews sang, "The beginning is a good place to start."

-To the love of my life and favorite life and travel partner: Tara, you joke often that you are earning the Mrs. Doctor degree alongside me. You already have it! Thank you for supporting me, proofreading my exciting…err boring papers, giving me the time to work diligently over the past five years, loving me, giving patience, and taking so many things off my plate to help me finish strong. This degree is as much yours as it is mine, and I am grateful to spend the rest of my life with you!

-To my boys: Caleb and Nathan, I do this as an example that you can accomplish anything you put your brilliant minds to. This was hard, but my desire to be a role model for your academic endeavors pushed me to the end. I love you both more than you will even know and am blessed to call you sons. May you impact the world in ways I cannot, and love others deeply!

-To my parents: Thank you for instilling in me a love for the Lord, family, striving to do things right, and a work ethic. The best parts of me are because of both of you, and I know I wouldn't be here today without your support and love. I love you Mom and Dad more than I can say.

-To my small group, thank you for providing an outlet each week for my stress. I am so thankful for the journey we are on and how I know I can rely on you for prayer and support for anything that arises. Thank you!

-To my wonderful OKC cohort members: We really are the best cohort ever…someone fight me on this one! Such a diverse group yet honestly bonded for life. *Janelle*, my fellow foodie…your gift of hospitality made the six hour (!!) Thursdays bearable. Thank you for graciously providing so many yummy treats. *Will*, you were such a great addition to the cohort, and I have enjoyed getting to know you through this process. I know great things are in front of you and your talent and gifts are immense. *Scott*, wow, you are definitely one of the deepest thinkers in the group! I miss your musings and humor…honestly one of the hardest things to give up once coursework ended.

**Acknowlegements reflect the views of the author and are not endorsed by committee members or Oklahoma State University.*

Niccole… one of the first cohort friends! I am so grateful to have had the pleasure of hosting your baby shower for the cohort and watching you grow as a mom and scholar/practitioner has been amazing. *Sam/Pam*, what can I say? I will never forget that May hybrid class where I read your online posts and was blown away by the depth and insight that, to date, was kept under lock and key! You changed my paradigm in a great way for online learning, and I cannot wait to see how you will rock the higher education world…your best days are definitely ahead of you with this degree! *Ray*, I will never forget the adventures we had to and from Thailand, in the back alleys of Songkhla, and the amazing Thai dinner we shared that night with our amazing hosts. You are one of a kind and I am so grateful this cohort brought us together. *Leslie*, what I say here depends…oh it all depends! I loved hearing your perspective on whatever topic is at hand. You have been so supportive from the beginning, and I was so happy to watch you become Dr. Cothren! *Brent*, I still remember the conversation in the caf at SNU where this OSU program began for us! The countless drives on Thursday afternoons (do we take Portland or I-44?) and evenings provided the support and routine that I needed to get through the five years. Thank you for that. Check. Check! *Zeke*, you are the rock of the cohort. I honestly have never met anyone quite like you, and I am grateful to know you. You are a counselor, advisor, expert student affairs professional and the first to finish. You paved the way from the first day we met to now. Thank you for all you have done for me and each of us along the way. *Michael*, who knew that a chance meeting at a Whataburger in Shawnee, OK with the question, "Do you work in Residence Life?" would turn into the friendship we have today. You are the best writing partner ever, you challenge me to see the world in amazing ways, you have a beautiful family and a zeal for life that is contagious! I am grateful for you and know that even though we are far in proximity, we are near at heart…finish strong! Wow, all of you are amazing and together we are powerful. Know I am only a phone call away!

-To my esteemed committee: We just might finally land this plane, and oh what a journey it has been. *Dr. Vogler*, I am so grateful to have you as my content expert. It was fortuitous that our paths crossed, and this project is better because of it. I value your insight and direction and thank you for your time serving on my committee. *Dr. Mwavita*, when I added you as my methodologist when my committee changed for a third time, I was at a near breaking point. You provided clear and calm direction to help me wade through the quantitative waters. I appreciate you adding me to your busy and already full plate, and I am grateful for the work you have done supporting my research and data analysis. *Dr. Wanger*, it's been quite the journey. I am indebted to you for planning and taking us to a newfound love, Thailand. Those ten days are etched in my memory forever and are a true highlight of the program. Also, thank you for coming to my house and opening your house for cohort gatherings. Your challenge, although not always easy, has pushed me to new heights, and I am grateful and thankful for this and for you! Dr. Kearney…*Kerri*, you made me come to class on a fall, football Saturday and do ART! Really? As I think back to that semester, I honestly learned more about myself in that course and each of your courses than probably anywhere else in my academic preparation.

Couple that with your willingness to step into my moment of crazy and wear the advisor hat, and my debt to you is large. You are a true blessing to me, and words cannot express my gratitude for all you have done. Thank you so much, and WE DID THIS! ☺

-To the amazing faculty at OSU, you challenged me with new perspectives, and helped me become a better writer, scholar, and practitioner. I will always be indebted to you for the time and wisdom you gave and hope to continue in your scholarly footsteps. *Dr. Z*, you showed me how a true scholar's mind works, and I am grateful for your feedback and the countless resources you provided. You were a springboard for this topic and project, and I hope our paths cross again. *Dr. Bailey,* the zest and fervor for life you brought each and every night of class was a gift! You brightened my life and I miss you. Know you are making a difference in this world, and I am just one example.

-Dr. Foubert, when I first heard you at the ACSD at Taylor, I knew our paths would cross again. Who knew that you would be my doctoral advisor? You were an amazing advisor in every sense of the word. You championed me, pushed me, provided timely feedback and life insight. I truly am sad that we could not finish together, but your fingerprints are all over this work. Thank you for giving of yourself!

A friend told me this was the most difficult section to write. I am now beginning to realize why. There is not enough room to continue to thank the countless people along this doctoral journey. So many have come alongside and provided support and insights. *Dr. Drabenstot* thank you for fielding my stats questions and verbally processing my alignment and questions. *Mary Eskridge* thank you for proofreading this beast of a project. *Scott and Mike* thank you for giving me the time to work on this degree and helping financially. *Chuck* if you know you know. *Kris* your friendship is special, and I am so blessed to have it, and to the rest of my family and friends who have supported prayerfully and financially, I complete this for you.

-Finally, "To Him who is able to do exceedingly abundantly above all that we ask or think, according to the power that works in us, to Him be glory forever and ever." Ephesians 3: 20-21.

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Date of Degree: DECEMBER, 2019

Title of Study: THE EFFECTS OF INTERNET ADDICTION ON COLLEGE STUDENTS: THE RELATIONSHIP BETWEEN INTERNET ADDICTION TEST SCORES, COLLEGE STUDENT DEMOGRAPHICS, AND ACADEMIC ACHIEVEMENT

Major Field: EDUCATIONAL LEADERSHIP AND POLICY STUDIES: HIGHER EDUCATION

Abstract: Modern technology has changed education in many ways in a very short time. Not only are college students using technology daily, technology innovations help educators reach broader audiences of students through online learning, and online portals help educators share course materials. Awareness of this modern technology and the impacts it is having on higher education and students has become a critical issue over the past two decades. Even though the benefits of technology are often visible, researchers are finding that technology is creating challenges for some students. Students' access to personal technologies has drastically increased, and with it the level of distraction, which competes with academic interests.

The purpose of this quantitative study was to analyze the relationship between the Internet Addiction Test (IAT) score and academic performance. The IAT measured the student's addiction to the Internet based upon his or her use. A student's academic performance was measured by grade point average. A sample of 692 traditionally aged college students from both public and private institutions was used to examine if IAT scores were related to and predictive of grade point average. Data analysis comprised four stages: descriptive, correlation, linear regression, and analysis of variance.

This study found a negative relationship was present between students' IAT scores and grade point averages. While the statistics showed that as IAT scores increased, students' grade point averages decreased, the overall affect was minimal. Better understanding of how Internet addiction is related to grade point average may prove helpful for higher education leaders. As technology innovations continue to rapidly increase, it is imperative that educators understand the relationship technologies have on college students.

KEYWORDS: Internet addiction; Technology addiction; Internet Addiction Test

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CHAPTER I

INTRODUCTION

If an individual were to walk across a college or university campus in the United States mid-morning between classes, find a central, highly trafficked location, and take a picture, there would be many similarities among pictures taken, despite the differences in institutions. The picture likely would be framed with buildings, possibly a library or student union. There would be manicured trees, bushes, and lawns. Sidewalks or pathways would be visible, and there would more than likely be students, many with backpacks or bags walking to and from class.

Interestingly, these same images would be evident if a snapshot were taken in a similar place throughout the decades of each institution. The style of clothing the students were wearing would change, and the color of the picture would change with age, but there would still be buildings, pathways, lawns, bushes, and students. One thing, however, would be drastically different in a picture taken today as compared to just twenty or thirty years ago.

Today, it would be very difficult to take a picture and not see technology in various forms. A contemporary picture would likely show many students with headphones or earbuds, talking into or looking at phones while walking. If students were sitting on the lawn or a bench, there would likely be a laptop or tablet computer visible. If pictures throughout the decades were lined up, the proliferation of technology in today's pictures would be striking.

Technology is a norm in contemporary society, and the use of technology in daily lives has grown at a breakneck speed (Derbyshire, et. al., 2013). This rapid growth, not only in the proliferation of technology but also accessibility throughout society, has provided little time to evaluate the benefits and potential negative effects, specifically in relation to college students. An example of a benefit technology provides education is in the way education is offered to students. More students have the opportunity to study today with online course offerings (Kenney, 2011; Kurt, 2010).

Even though the benefits of technology are often easier to witness, researchers are also finding that technology is creating challenges for students. Students' access to personal technologies has drastically increased, but also the level of distraction, which competes with academic interests (Schmitt & Livingston, 2015; Yao & Zhi-jin, 2014). Although historically, many studies examined the relationship between student demographic factors such as sex, major, and academic performance, the predominance of Internet use potentially introduces a new variable for researchers studying college student engagement and success. Thus, this chapter presents a research design aimed first at analyzing the relationship between student academic success as measured by grade point average and Internet Addiction Test scores, as measured by the Internet Addiction Test. Next, the design explores if a student's score on the Internet Addiction Test is predictive of grade point average. Finally, the study analyzes if there is a difference between student demographic variables of sex, research site, race and student classification and Internet Addiction test scores.

Problem Statement

From books, to chalkboards, to television, to modern day tablet computers, smartphones and smart boards in the classrooms, technology innovations impact the higher education community (Haran, 2015). One visible change technology has on education is how instruction is provided to students. Online instruction has increased across higher education institutions at rapid rates and allows colleges and universities to reach populations of students unable to attend brick and mortar campuses (Kenney, 2011; Kurt, 2010; Lin & Yang, 2011; Mango, 2015). Additionally, technology innovations have impacted web portals, course management, and learning systems in higher education. Studies show that each of these innovations enhanced student learning and persistence (Christen, 2009; Costley, 2014; Keser, Uzunboylu & Ozdamli, 2012). Current literature also highlights the positive relationships between technology and student engagement, student confidence, and motivation (Costley, 2014; Kenney, 2011; Lin, & Yang, 2011).

However, studies are also revealing negative effects of technology use on college students and challenging many of the positive presuppositions of educators regarding the use of technology in educational settings (Edwards, 2015; Fried, 2008). Compared to previous generations, college students today spend less time studying (Arum & Roska, 2011) in lieu of the many distractions vying for their time, and technology use is one of the most glaring. Indeed, many 21st century students are becoming addicted to technology (Agarwal & Kar, 2015; Young, 1998). Technology addiction is a psychological dependence on technology and is characterized by increased investment of time on technological pursuits (Nalwa & Anand, 2003; Young, 2008). College students are entering institutions addicted to technology at rates that far outpace previous generations (Christakis et. al., 2011). Their addiction may inhibit their intended learning outcomes in higher education (Agarwal & Kar, 2015; Young, 1998).

Students exhibiting signs of technology addiction show decreases in student success and persistence in higher education (Krumrei-Mancuso, Newton, Kim, & Wilcox, 2013). Additionally, a student's use of personal computers, smartphones, and video games are linked with negative psychosocial behaviors which impact student learning (Heyoung, Heejune, Samwook & Wanbok, C., 2014; Hui-Jie, Hao-Rui & Wan-Seng, 2014; Schmitt & Livingston, 2015; Yao & Zhi-jin, 2014). Furthermore, neurology research is revealing relationships between extended technology use and negative impacts on brain chemistry and development (Liu et. al., 2015). In summary, scholars suggest that technology use may have negative impacts on student engagement, learning, and persistence in higher education today (Christakis et. al., 2011; Edwards, 2015; Fried, 2008). Further research is needed to determine how technology addiction is impacting college students' academic performance along with the relationship of student demographics to technology addiction.

Purpose

The purpose of this quantitative study was to analyze the relationship of the Internet Addiction Test (IAT) score and academic performance and identify difference between student demographic variables and IAT scores. This study used Young's (1998) Internet Addiction Test (IAT). The IAT score was used to determine a student's addiction to the Internet. A student's academic performance was measured by grade point average. A student's demographics included sex, research site, race, and student classification.

Research Questions and Hypothesis

Following the review of the literature and utilizing two theoretical frameworks (rational addiction theory and distraction conflict theory), the following research questions and hypotheses were created to guide this study:

Research Questions

RQ1: *"Is there a relationship between a student's Internet Addiction Test (IAT) score and grade point average?"*

RQ2: "*Is there a mean difference among sex and IAT score?"*

RQ3: "*Is there a mean difference among research site and IAT score?"*

RQ4: "*Is there a mean difference among race and IAT score?"*

RQ5: "*Is there a mean difference among classification and IAT score?"*

Hypotheses

RQ1: H0/Null hypothesis: There is not a significant relationship between IAT score and grade point average.

RQ1: Ha/Alternate hypothesis: Students' scores on the IAT are significantly related with grade point average.

RQ2: Ho/Null hypothesis: There is no significant difference of means of IAT score and sex.

RQ2: Ha/Alternate hypothesis: There is a significant difference of means of IAT score and sex.

RQ3: Ho/Null hypothesis: There is no significant difference of means of IAT score and research site.

RQ3: Ha/Alternate hypothesis: There is a significant difference of means of IAT score and research site.

RQ4: Ho/Null hypothesis: There is no significant difference of means of IAT score and race.

RQ4: Ha/Alternate hypothesis: There is a significant difference of means IAT score and race.

RQ5: Ho/Null hypothesis: There is no significant difference of means of IAT score and student classification.

RQ5: Ha/Alternate hypothesis: There is a significant difference of means of IAT score and student classification.

Design Overview

This study was positioned in an objectivist epistemology with a post-positive theoretical perspective. An objectivist epistemology posits that meaning exists independently from human conscience (Crotty, 1998). Furthermore, the post-positive assumptions are that there is an objective truth, however that knowledge relies on human conjecture and experience, and thus it is difficult to find absolute truth (Creswell, 2014). For this study, the researcher chose a quantitative design which sought to find relationships between students' Internet Addiction Test scores and a student's academic performance as measured by grade point average. Additionally, the study examined if IAT scores influenced a student's grade point average. Finally, the study analyzed if there was a difference in means between student demographic variables of sex, research site, race, and student classification and IAT scores.

The population consisted of traditional college students from three institutions in a south-central region of the United States. One, four-year, large research institution, and two regional, liberal arts institutions. Students from these institutions received an online questionnaire through email. Data were collected from April 2019 through June 2019. Four types of data analysis were conducted analyzing the research questions: Descriptive, correlation, OLS test (linear regression), and analysis of variance (ANOVA). A more detailed discussion of the design for this study is provided in Chapter Three along with the statistical analysis in Chapter Four.

Definition of Terms

Technology Addiction

Addiction to technology is a psychological dependence on Internet technology and is characterized by an increased investment of personal resources such as time and money on Internet related activities (Nalwa & Anand, 2003). In the literature, technology addiction and Internet addiction coincide and are used interchangeably.

Problematic Internet Use

The research community is split on what terms are used to describe an individual's excessive use of technology. Whereas some use the terms Internet or technology addiction, others prefer to use Problematic Internet Use because it is believed that the individual is not addicted to the Internet itself, rather, they have deeper addictions such as gambling or pornography and the Internet is just a means to feed these addictions (Caplan, 2002; Davis, Flett, & Besser,2002; Erickson, 2008). With the literature using Internet addiction more frequently and DSM 5 recognizing Internet Gaming Disorder for the first time, this study used Internet addiction.

Multitasking

Multitasking refers to the brain switching back and forth between focal points or switching between multiple forms of information at one time (Junco & Cotten, 2012). Multitasking is a critical component of this research, as students are increasingly challenged to switch between nonacademic and academic tasks, oftentimes due to the available technology present (Ophir, Nass, & Wagner, 2009).

Digital Natives

The term many researchers use for 18-29 year olds, comprising today's traditional college students, is digital natives (Bowe, & Wohn, 2015; Dede, 2004; Prensky, 2001; Tapscott, 2009; Thompson, 2013). Digital natives grew up with computers in the home and in school and had various forms of technology at their disposal. Additionally, the smart phone and social media were introduced when they were very young (Christakis et. al., 2011). This saturation of technology throughout a younger person's life, both socially and academically for example, is a marker of this generation (Rideout, Foehr, & Roberts, 2010; Thompson, 2013).

Some scholars question the desire digital natives have for lives completely enmeshed with technology (Friedl & Vercic, 2011). Furthermore, studies are trying to determine if there is a significant difference in learning preferences between digital natives and previous generations (Bowe & Wohn, 2015). Even with these disparate examples, the body of literature pertaining to digital natives is continuing to grow and show that this generation of college students is influenced by technology in the way they learn, process information, and interact socially (Barak & Dori, 2009; Tapscott, 2009; Thompson, 2013).

Cyber Slacking

Cyber slacking is a term used to describe students using technology for nonacademic purposes (Gerow, Galluch, & Thatcher, 2010).

Significance of Study

The topic of technology usage and student demographics and learning is still in its infancy. With the smartphone barely a decade old, there are limited empirical and longitudinal studies focusing on the impacts of technology use on student learning, persistence, and success. The significance of this study addressed three important criteria: significance in the body of literature and research, significance in relation to theory, and significance in relation to practice.

Research

Researchers have studied academic achievement for decades specifically focusing on the demographic differences of college students in relation to student success and retention (Astin, 1964; Astin, 1997; Bayer, 1968; Braxton, 2000; Tinto, 1987; Tinto, 1998; Vaughan, 1968). The primary demographic metrics presented throughout the literature used to study academic achievement are race, sex, and grade point average (Reason, 2009). In addition, researchers have studied a wide array of other variables seeking to find predicting variables for student success. Some of these include age, economic class, academic preparation, and declared major to name a few (Keller, 2001; Murdock & Nazrul Hoque, 1999; Reason, 2009).

Pascarella & Terenzini (1998) recommended that with the ever-changing demographics within higher education, researchers should continue to change how, who and why to research the student population. Furthermore, it is vital that, with the increasing diversity in college students, researchers should attempt to understand how predicting variables interact with each other. Although the literature is relatively shallow on the topic of modern technology use related to academic performance, studies are starting to reveal that there may be some serious issues pertaining to technology use and the implications this use may have on academic performance.

The outcomes of this study contribute to current literature presenting that modern technology use might be a wolf in sheep's clothing; technology generally is accepted as a positive addition in educational settings, even though scholars are beginning to better understand the underbelly of modern technological inventions. These innovations create, for some, a tension to focus, higher levels of stress, and depression--which all can negatively impact a student's ability to complete academic tasks and persist. The findings of this study are intended to offer insight into the relationship between IAT scores and student success as measured by grade point average. Findings also discussed the differences between student demographics of sex, research site, race, and student classification, and IAT scores.

In addition to contributing to the understanding of links between demographics and IAT score, and IAT scores and academic performance, longstanding theories of student learning and engagement are also challenged. The following section continues this discussion.

Theory

Multitasking research and theories are not new. In fact, researchers have studied and theorized about multitasking for over half a century (Craik, 1948; Navon & Gopher, 1979; Telford, 1931; Welford, 1952). Additionally, researchers have studied the way students engage and process information in academic settings for decades (Biggs 1987; Biggs & Telfer 1987; Bronfenbrenner 2001; Martin et al. 2012). The introduction of personal technologies is creating a new variable in the discussion of learning and focus. This new variable may begin to challenge many of the conventional theories of learning, distraction, and multitasking.

The findings of this study attempted to provide further evidence supporting the distraction conflict theory pertaining to the tension created by distractions relating to student academic achievement. Additionally, the study expanded the use of rational addiction theory to include Internet addiction and explained why students may choose to use the Internet over accomplishing academic tasks, thus hindering academic performance.

Not only is the topic of how technology use differs among student demographics along with the impacts on academic performance pertinent to the body of literature and theory, it is also critical to better understand the relation to practices in higher education. The next section further discusses the intersections of technology and higher education practice.

Practice

Technology is challenging the way educators provide information to students (Engstrom, 1997; Ragan, Jennings, Massey, & Doolittle, P., 2014). Although technology has created numerous mediums for the distribution of material, technological advancements also are creating more points of distraction for college students. The literature is beginning to show that these distractions are challenging college students' focus and potentially inhibiting the ability to accomplish academic tasks (Gerow, Galluch, & Thatcher, 2010). Additionally, students are showing evidence of interpersonal struggles along with mental health issues rising from excessive technology use.

Thus, the topic of technology use and its relationships with both student demographics and academic performance is significant to practice in higher education. While study findings showed that IAT scores are significantly related to grade point average, however, significance was not such that the instrument can be recommended as a predictor to academic success as measured by grade point average. The researcher recommended further exploration and development of other instruments for assessing the addiction levels of college students. Doing so would help college leaders identify students who may struggle early in college due to personal technology use and devise interventions to support their success.

Research Statement

As a higher education practitioner for twenty years, the researcher noticed the increased use of technology by college students. Early in the researcher's career, it was the video gaming consoles that challenged students' time. There was a time when a new version of the video game 'Halo' came out and the researcher had to meet with students about skipping class too often because of gaming. Next, when the iPod was introduced, it seemed like every student got one over the holiday break. For the first time, the researcher watched countless students walking across campus with ear buds in their ears.

Then, a little over twelve years ago, in 2007, Apple released the iPhone and the game changed. A colleague in Seattle, WA called the smartphone the world's longest umbilical cord because students were connected to their parents more than ever. Also, students seemed to constantly be on the phone...in class, at sporting events, in the cafeteria, at student events. All of this led the researcher, and fellow colleagues, to begin technology 'fast' weekends, encouraging students to take a break from technology for everything other than homework.

While sitting at lunch with a mentor in 2006, she said something that is still haunting. She said, "It takes up to twenty years for some foods or drugs to get through testing and regulation before we can ingest it. However, Microsoft can roll out the newest version of Windows and push updates to our computers overnight, and we all ingest it without much thought, and with very little regulation or testing."

The question that has been mulling in the researcher's mind for some time: What is all this modern technology doing to students? This has been the driving question throughout this doctoral program and is why the researcher chose this perspective for this dissertation. Anecdotally, the researcher has noticed changes in students over the years, but as a scholar/practitioner in training, the researcher began this doctoral program searching for literature and answers to the growing technology phenomenon. This study was a culmination of this quest.

Chapter Summary

With the rapid growth of technology innovation, the researcher was concerned that scholars are not truly able to keep up with the changes that are pumped out by technology giants and consumed by students. As the literature is beginning to show, technology use, while having plenty of positives, also has negative impacts. These negative impacts have arguably not received enough attention. This study intended to explore the student scores on the Internet Addiction Test and how they are related to student demographics and academic achievement as measured by grade point average. The findings of this study are added to the body of literature and may provide valuable opportunities for practitioners to intervene.

The next chapter, Chapter Two, provides a review of the literature examining technology in higher education and the implications of academic achievement. Chapter Two more thoroughly explores college-aged young adults (digital natives) with a discussion of demographics, an examination of the use of grade point average (GPA) to measure student achievement, multitasking literature, and both positive and negative impacts of technology on student learning and achievement. Furthermore, primary theories for this study are presented along with an analysis of inventories used to assess technology use. Chapter Two concludes with a discussion of Internet Addiction and Problematic Internet Use.

CHAPTER II

REVIEW OF LITERATURE

From 2000 to 2015, the Pew Research Center conducted a longitudinal study analyzing technology use in the United States. The findings presented rapid growth in the innovation, sales, and usage of technology (Perrin & Duggan, 2015). This technology surge was also evident across institutions of higher education. During this time, U.S. colleges and universities began implementing and utilizing technology throughout all areas of higher education (Christen, 2009; Costley, 2014). Whether laptops used in the classroom, online learning modules and courses enhancing distance learning, or online discussion groups and group projects, technological advances are impacting education.

Additionally, both Educause and Pew Research reported that almost all college students accessed the Internet, used social network sites, and connected wirelessly with cell phones, tablets, and other personal computing devices (Hakoama & Hakoyama, 2011). In 2009, roughly ninety-five percent of college aged adults, categorized as ages 18-29, used the Internet. This was an increase from seventy-four percent at the turn of the 21st century (Derbyshire, et. al., 2013). Furthermore, in 2011, thirty-eight percent of students reported they could not go more than ten minutes without checking some form of technology, and seventy-three percent reported that they needed technology in order to study (Kessler, 2011).

Not only are college students using technology daily, technology innovations help educators reach broader audiences of students through online learning, and online portals help educators share course materials. Modern technology has changed education in many ways in a very short time. Awareness of this modern technology and the impacts it is having on higher education and students has become a critical issue over the past two decades.

For the purpose of this study, a review of the literature focuses on the following topics: student demographics, academic achievement and grade point average, contemporary college-aged young adults (digital natives), how digital natives utilize technology, multitasking literature, technology and the positive impacts on student learning, technology and the negative impacts on student learning, primary theories informing this study, analysis of inventories available to assess technology use, and Internet Addiction and Problematic Internet Use.

Although technology innovations are not new to education, the rate of change of technology innovations is arguably as rapid as it has ever been. The swift increase of technology use in society, and particularly in higher education, has created a need for researchers to study how technology use affects college students. With the ever-changing technology landscape, researchers are beginning to provide insights into the impact of technology on higher education and higher education students. The following sections explore this important topic, beginning with a better understanding of traditional, student demographics used to measure academic achievement.

College Student Demographics

Studying the demographic differences of college students and how those differences relate to academic achievement is not a new venture. For almost seventy years, researchers have sought to better understand not only why students progress through college, but also the make-up of successful college students. From seminal studies by Astin (1964) to Vaughan (1968) to Tinto (1987; 1998), demographics play a large role in the understanding of student engagement, persistence, and ultimately academic achievement. Large sections of literature continue to highlight some primary demographics. Whereas there are many additional demographic categories, these primary demographic variables were used for this study and are discussed in this review of literature. The primary demographic variables are sex, classification, race and grade point average.

Sex

For numerous decades researchers have studied how males and females persist through higher education. Early studies posited that sex was a significant factor in college student persistence and achievement (Astin, 1975; Astin, Korn, & Green, 1987; Tinto, 1987). These studies found that sex was a significant variable in student achievement and that women were more likely than men to persist in college.

Around the turn of the century, studies began to find less significant results when sex was combined with other variables such as grade point average and race. Reason (2001) and St. John et. al. (2001) found that gender by itself was a significant variable, however, other variables interacted with gender causing gender not to be a significant predictor variable when race, age and grade point average were included. These researchers challenged future studies to continue to use gender as a predictor variable, however, to not focus on gender exclusively, but include other variables to get a better understanding and accuracy of results.

Classification

Numerous studies report that classification is a predictor variable of student success, even among traditional college students (18-25). This study uses the following classifications, 1st year students, 2nd year students, 3rd year students, and 4th year or more students. Students were asked to select which year in college they were when taking the survey.

Classification is shown to be a significant variable in researching student persistence and achievement (Mayhew, et. al., 2016; Pascarella & Terenzini, 1998). Pertaining to technology use, students appear to use lower levels of non-academic technology as they matriculate through college (Junco, 2015). This study used classification as a demographic variable and explored the relationship between a student's classification and IAT score. Sex and classification are two of the primary demographic variables used when studying college students. The next variable is race.

Race

Throughout the literature, race and ethnicity often are conflated (Reason, 2009). Although race is different from ethnicity in that race refers to a person's physical characteristics compared to ethnicity which refers to cultural factors represented in a person; for clarity's sake and alignment with the literature, race is used in this study. Research has found that race is a statistically significant predictor of student achievement and persistence (Peltier et. al., 1999, Reason, 2009). Whereas the issues are more complex than just the race students are born into, African American, Hispanic, Native American and Pacific Islander students all tend to perform at lower levels academically and persist at lower rates when compared to Asian and White students (Murtaugh, et. al, 1999; Peltier, et. al., 1999; Reason, 2001; Reason, 2009). It is important to understand how students from different races are impacted by Internet addiction, thus the inclusion in this study. A fourth and final variable used in this study is grade point average.

Grade Point Average (GPA)

Grade point average, while criticized for its true representation of student capability or knowledge, is a metric generally accepted across higher education for gauging academic achievement. The literature shows that grade point average is a significant variable in studies analyzing student persistence and achievement. First-year GPA, along with high school GPA and cumulative college GPA all have been shown to predict college student achievement (Reason, 2001; Reason, 2009, St. John, et. al., 2001). Studies show that students with higher grade point averages at all levels of education have higher levels of academic success as compared to students with lower grade point averages.

As with the previous three demographic variables, GPA should not be a standalone variable and researchers recommend that other variables be used with GPA to help find significant results (Reason, 2009). For this study, a student’s cumulative grade point average was analyzed along with a student’s IAT test score to explore the relationship between IAT score and GPA. Each of the demographic variables were used in this way to explore any relationships between them and a student’s score on the Internet Addiction Test.

For this study, students self-reported GPA. Although some question the validity of self-reported GPA, decades of literature provide support that self-reported GPA, particularly in college student populations, is as valid an indicator of future success as actual grade point average (Baird, 1976; Cole & Gonyea, 2010; Schwartz & Beaver, 2014; Sticca, et. al., 2017; Stone, et. al., 1999; Talento-Miller & Peyton, 2006).

These primary variables, along with student classification and research site, comprised this study. The following section of this review of literature provides a better understanding and description of the contemporary college student. Many researchers are calling traditionally aged students today 'digital natives' and these students are discussed below.

Digital Natives

Contemporary, traditional college students have grown up in a world surrounded by numerous forms of technologies. Throughout their lives, computers have been accessible in the home, at school, or in libraries and, at a young age, the smartphone became a part of daily life. Many researchers call current 18-29 year old's "Digital Natives" (Bowe, & Wohn, 2015; Dede, 2004; Prensky, 2001, Thompson, 2013). This age group is saturated with technology (Bowe, & Wohn, 2015; Rideout, Foehr, & Roberts, 2010; Thompson, 2013).

Growing up with access to technology, and a level of competence with various types and forms of technology, may lead to an assumption that digital natives are able to handle the demands of technology and better understand it, as it relates to multitasking. Even though the broad characterization of technological fluency in this generation is generally accepted, scholars are finding the technological competency gap between digital natives and older generations might not be as broad as expected (Bowe, & Wohn, 2015; Thompson, 2013).

The literature shows while comparing college students under the age of 25 with university faculty over the age of 25, there are minimal differences in the technologies embraced and general competencies of technology use (Kennedy, Dalgarno, et al., 2008; Kennedy, Judd, et al., 2008). Furthermore, when a broader age group of students focusing on technological competencies was studied, with students ranging from age 20 to 40, no statistical differences were found among the age groups (Guo, et.al., 2008).

Even with the differences smaller than anticipated between the digital natives and previous generations, researchers are finding digital natives have some distinguishable characteristics, and it is imperative that contemporary higher education leaders understand these characteristics, which provide a better understanding of contemporary traditional students and how they interact. The following section discusses the characteristics of digital natives outlined in research, looking at both potential positive impacts on learning and some risk factors.

Immediate Gratification for Effort

Digital natives are accustomed to receiving instant gratification (Bowe, & Wohn, 2015; Prensky, 2001). Video games, social media posts, and short video vignettes produce instant results and/or positive reinforcements. This immediate gratification creates similar desires in educational settings (Bowe, & Wohn, 2015; Prensky, 2001; Rosen, 2010). This desire for instant gratification can be a strong motivational tool in the classroom. Students prefer environments that create immediate feedback, and students strive to gain this feedback and work through tasks quickly (Bowe, & Wohn, 2015;

Prensky, 2001; Rosen, 2010). However, this desire for instant feedback can also create boredom and students are showing lower levels of perseverance or grit through difficult tasks, which may inhibit learning (Crede & Kuncel, 2008).

Desire for Speed and Frustrations with Slow-paced Environments

College students have grown up with the speed technology provides and have become accustomed to fast paced environments. Studies find that their desire for a quicker pace created students who can scan information and process it more quickly than previous generations (Dede, 2004; Prensky, 2001). A potential risk for this fast-paced desire may be witnessed in students who struggle with critical thinking and the ability to think abstractly. This is partially because fast-paced society oftentimes is in stark contrast to the slower pace of academic exploration and learning. Additionally, students' desires for speed might limit abilities to critically analyze and reflect when presented with more challenging content (Carr, 2010; Small & Vorgan, 2008).

Challenged to Multitask

For digital natives, the pressure to multitask arguably is amplified because the pace of life created by newer technological innovations and accessibility is brisk. With all the demands for attention, many created by technology, students are constantly making decisions on what gets their attention (Bowe, & Wohn, 2015; Prensky, 2001; Rosen, 2010; & Tapscott, 2009). The wide array of these demands for attention may help limit an individual's boredom, and studies find that digital natives are able to regulate multitasking better when compared to previous generations (Prensky, 2008; Rosen, 2010). However, as is discussed later in the multitasking section of this literature review, researchers are also finding many detriments when students attempt to multitask.

Multitasking can interfere with memory, which leads to lower academic performance (Hembrooke & Gay, 2003; Fried, 2008). Additionally, students who multitask report that they study less (Bowman, et. al., 2010, Fried, 2008). This lack of study time hinders academic success compared to students who study longer (Bowman, et. al., 2010, Fried, 2008). Also, digital natives who claim to multitask report higher levels of mental exhaustion as compared to peers who multitask at lower levels (Small & Vorgan, 2008).

More Pictures, Less Text

Students report higher levels of affinity in learning environments with more pictures and less text. This is especially true with online material (Tapscott, 2009). The desire for more pictures is creating higher levels of visual and spatial skills in digital natives (Prensky, 2001; Tapscott 2009). However, like a student's desire for fast-paced environments, the desire for pictures also may limit deep, reflective reading and critical thinking skills (Carr, 2010).

Nonlinear Information Processing

Many scholars have studied the notion that learning can happen through many different platforms and through many different systems, as compared to previous decades. Technology has provided this learning enhancement and digital natives are now learning in nonlinear ways (Bowe, & Wohn, 2015; Dede, 2004; Tapscott, 2009). Using technology, students can find information quickly and from numerous sources. This simultaneous exploration may create greater understanding of complex ideas (Tapscott, 2009). A risk, however, is that when digital natives use nonlinear thinking they may struggle when presented with tasks requiring linear thinking, such as accounting, forensics, and even scientific experiments (Carr, 2010).

Collaborative Learning and Constant Connectivity

College students are growing more collaborative and seek collaborative learning environments at greater rates (Rosen, 2010; Tapscott, 2009). Technological advances have largely fueled this desire for collaboration (Rosen, 2010). Students can work collaboratively outside of the brick and mortar education structures of the past. This collaboration inspires learning and teamwork and creates projects that might have been difficult to accomplish in previous generations (Prensky, 2001; Tapscott, 2009). A potential risk presented when using technology for connection is the distraction of available online socializing methods. Students report distractions, from social media for example, when studying and working online (Bauerlein, 2008). These distractions tend to limit academic success (Fried, 2008).

Learning by Doing Rather Than Lecture or Reading

Due to collaborative approaches educators create for college students, digital natives may experience gains in active learning. A benefit to this desire for active learning is that students are not waiting for instruction and are taking more responsibility for learning (Prenski, 2001). However, some students are becoming more apprehensive to traditional instructional approaches such as lectures or presentation, thus many important concepts and steps exposing essential content may be missed (Mayer, 2004). Furthermore, studies have shown digital natives struggle to learn in non-active settings (Tapscott, 2009).

Balancing Time between Work, Play and Leisure

Digital natives appear to manage the demands of balancing schedules well (Ito, et. al., 2010). Students mix work and play and use time well to complete tasks. Studies show that mixing work and play can create more imaginative problem solving which ultimately enhances learning (Ito, et. al., 2010). However, at times, this desire to mix work and play creates an expectation for entertainment in the educational setting (Crede & Kuncel, 2008). This expectation may inhibit learning and create impatience in form academic settings (Crede & Kuncel, 2008; Mayer, 2004).

Expectation for Technology in Educational Settings

Contemporary students are demanding more technology integration in learning settings. This trend has been growing for two decades (Dede, 2004; Prensky, 2001; Tapscott, 2009). Much of this is rooted in the students-as-consumers literature. Digital natives have grown up in a buy-and-consume society (Hill, 2011). Therefore, students-as-consumers often expect colleges and universities to meet their needs and desires. This includes providing not only wireless networks, but also allowing the use of technological devices (Delucci & Korgen, 2002; Hill, 2011; Obermiller & Fleenor, 2005). Students who believe they are entitled to technology use do not feel remorse when cyber slacking. Consumers believe that they are paying for college and can use technology as they please (Taneja, Fiore, & Fischer, 2015).

Educators who implement technology into pedagogy are showing positive results to student engagement and learning (Mishra & Koehler, 2009; Mishra & Koehler, 2010). However, with the implementation of technology, researchers are finding that higher levels of distraction are present with multiple streams of information present at one time

(Bellur, Nowak, & Hull, 2015; Cerretani, Iturrioz, & Garay, 2016; Junco, 2012; Zhang, 2015). This distraction is leading to higher levels of cognitive load, which limits effective learning (Nicholson, Parboteeah, Nicholson, & Valacich, 2005).

Social Norms and Students as Consumers

Digital natives are surrounded by peers using technology. Technological devices and use have become a social norm for this generation of college students (Gerrow, et. al., 2010). An individual's environment helps provide boundaries about what is acceptable or not. As it pertains to technology use, “Everyone is doing it.” Digital natives see this technological norm and conform. When friends are cyber slacking in class for non-academic purposes, a student is more likely to conform to this behavior out of a form of peer pressure, even though they individually might believe this behavior to be unproductive (Taneja, Fiore, & Fischer, 2015).

Each of these general characteristics provides better understanding into the makeup of digital natives. A common thread throughout the digital native characteristics is that of technology creating distractions and the desire to multitask. A recent study found that even digital natives, who have high levels of competence with various forms of technology, are not able to perform well in tasks requiring multitasking with technology (Muhterem & Yavuz, 2016). The study found if traditional students (18-29 years old) did not have the ability to pause one technological activity or another, levels of content retention of both information sources deteriorated (Muhterem & Yavuz, 2016). Furthermore, the same study found that concurrent multitasking with technology in a classroom setting limited the engagement of the student to the class and the content presented. When one information stream was paused, either the lecture or the informational technology, learning increased (Muhterem & Yavuz, 2016). This study aligns with the research on cognitive psychology and multitasking as previously presented. The following section will present literature that strongly presents that human cognition is not designed to multitask. Researchers are finding similar results when it comes to multitasking with technologies.

Technology and digital natives are connected, but the contextualization of these complex connections is imperative for future research. As mentioned previously, technology distractions often create environments where students are challenged to multitask. Much of the literature regarding technology use relates to multitasking. Students face the challenge of numerous streams of information bombarding them throughout the day, even in educational settings. Multitasking research is not new, however, it is important to cover as it relates to this discussion of technological impacts to educational success. The following section discusses the notions of multitasking and how a student's brain is challenged when presented with numerous information streams at one time.

Multitasking

It would be remiss not to address the literature pertaining to multitasking and the brain's ability or inability to multitask. With the rise of technology throughout society, researchers have honed in on the notion of divided attention, or multitasking. Multitasking is defined as, "divided attention and non-sequential task switching for ill-defined tasks as they are performed in learning situations" (Junco & Cotten, 2012, p. 505–506). Described another way, multitasking is switching among different types of media or exposure to various sources of information at one time (Ophir, Nass, & Wagner, 2009). These definitions encapsulate much of the psychological research analyzing the brain's ability to focus on different tasks.

To understand multitasking better, it is important to analyze the way human cognition works. The Adaptive Control of Thought-Rational model, created by J.R. Anderson (2007), describes human cognition as independent but interacting thought modules. These thought modules are called threads, and each thread can contain active tasks. Although the threads all run parallel with each other, Anderson (2007) posits that only one thread can be active or executing at any given time.

Even though some studies show that multitasking may not be detrimental to routine or familiar tasks that require minimal cognitive effort (Just, Keller, & Cynkar, 2008), most of the research finds that multitasking is very difficult at best, if not impossible to do. The human brain is not adept at processing multiple streams of information at once (Marois & Ivanoff, 2005; Monsell, 2003; Ophir, Nass, & Wagner, 2009). The challenge for the brain, when it comes to multitasking, is that multitasking challenges both working memory and processing. Multitasking becomes detrimental to learning when the brain's cognitive resources are depleted or limited due to the amount of information bombarding the brain (Kraushaar & Novak, 2010). Additionally, learning, especially more complex problems, requires a high level of cognitive processing (Mayer, & Moreno, 2003). The high level of processing required, alongside the brain struggling with multiple forms of information at once, all but eliminates the ability to multitask. Furthermore, when the amount of information and complexity of task exceeds the brain's capacity, an individual's ability to learn diminishes, along with lagging performance related to the task (Mayer, & Moreno, 2003).

In relation to this study, the research pertaining to multitasking is important because it helps shine light on the effects of students using technology while attempting to complete academic tasks. Previous studies have uncovered that students attempting to multitask experience distractions during lectures, and exhibit lower levels of success in the academic setting (Bellur, Nowak, & Hull, 2015; Cerretani, Iturrioz, & Garay, 2016; Junco, 2012; Zhang, 2015). These lower levels of success may be partly due to a lack of efficiency or a depth of learning. Students who multitask take more time to complete projects when compared to students who focus on a single task (Courage, et. al., 2015). Furthermore, students who are multitasking have a difficult time getting beyond superficial learning and into a deeper understanding of presented content (Courage, et. al., 2015).

Understanding the literature on multitasking helps provide a foundation for the struggles students may find using technology in educational settings. Additionally, the literature is clear that technology has affected the way digital natives learn. What is still unclear, however, is to what degree these technological impacts are positively or negatively impacting learning. It is important, however, that researchers continue to study this generation of students and how the broad array of technological innovations are influencing digital natives. The following section better examines the positive and negative impacts of technology on today's college students.

Positive and Negative Impacts of Technology Use and Student Success

The modern technology phenomenon is still in its infancy, with most of the explosion happening in the past ten to fifteen years largely due to the creation of the iPhone and social networking sites like Facebook (Christakis et. al., 2011). With this growth in technology use, the literature discussing college student technology use and the impacts on student learning is divided and relatively shallow. Chen and Peng (2008) found that heavy Internet users, with more than thirty-four hours of online activity per week, had lower grades as compared to students who used the Internet less than thirty-four hours per week. This technology use is depicted as general use, which included both academic use and non-academic time spent on the Internet. Conversely, Keyser, Wentworth, & Middleton, (2014) conducted a literature review with mixed results on the negative effects of technology use on academic performance. The following sections outline studies and findings on both the positive and negative impacts technology use has on student learning and success.

Technology and Positive Impacts on Student Learning

Technology innovations affect higher education from course offerings, to the way business is conducted, to the way students learn. Technology has greatly influenced the presentation of knowledge and course material, the evaluation of activities and courses, the business of the university, and the ways in which research is conducted (Engstrom, 1997). It is evident that educators, administrators, and students use technology across higher education.

How education is offered or provided to students significantly changed with the introduction of technology to higher education (Adams et. al., 1999). Historically, in order to go to college, students had to attend brick and mortar classrooms. Currently, technology is bringing college students and higher education together, with colleges offering increasing numbers of programs online and through distance learning (Kenney, 2011; Kurt, 2010).

Contemporary educators have a wide-range of technological devices and technology infrastructures at their disposal. Technology provides educators with countless teaching resources aimed at reaching a diverse body of students, across many platforms, and in many locales. Because of this technology, innovations on college campuses have positively impacted student learning in the 21st Century (Christen, 2009; Costley, 2014). Studies have found technology use creates more highly motivated students. In addition, students who moderately used technology reported higher levels of confidence and self-efficacy related to the availability of technology when compared to peers using lower levels of technology (Kenney, 2011; Lin & Yang, 2011). Furthermore, students using laptops in class for coursework are more attentive and engaged. Students claim that having the ability to supplement discussion and in-class lectures or presentations by using a laptop helped to synthesize the material and provided opportunities for deeper learning to occur (Samson, 2010).

Throughout history, technology has impacted higher education in major ways and continues to do so (Haran, 2015). The ever-increasing pace at which modern technology innovations are rolled out to society, and specifically education, is challenging higher education practitioners and researchers to better understand the benefits technology offers. Higher education practitioners, administrators, and scholars must have awareness of the role technology plays in setting direction for institutional agendas and educational outcomes. Even with all the benefits technology provides higher education, researchers are beginning to unveil a darker side of technology in relation to college students. The following section addresses the emerging issues.

Technology and Negative Impacts on Student Learning

Over the past decade, literature started to reveal that technology used in education does not always render positive outcomes. Students are using personal technology in the classroom more today than in previous years (Adams, 2006; Fried, 2008). Technology used for non-academic purposes in class is called cyber slacking. Cyber slaking creates distractions that may affect focus and, therefore, learning (Gerow, Galluch, & Thatcher, 2010). This section will analyze cyber slacking behaviors, specifically laptop use and mobile phones, time spent on technologies, depression and stress levels created by technology, and social media use and negative impacts.

Laptop computers. For years, researchers studied personal laptop use and the implications this use had on student learning and performance. Students have been using laptops in class since the mid-1990s (Adams, 2006; Barak, Lipson, & Lerman, 2006). One study showed that thirty-two percent of students said they used laptops for note taking. This same study also explored non-academic laptop use and found that fourteen percent of respondents said they used social media on laptops during class, while thirteen percent surfed the web (Ragan, Jennings, Massey, & Doolittle, 2014).

The topic of using laptops in the classroom and impacts to learning, however, is not as clear-cut as it might appear. Students report using laptops for both academic and non-academic tasks in the academic setting. Students use laptops to take notes and work on class projects germane to the course. Students can use online resources and computer-based tools to help supplement learning, and laptops actually help students take ownership in learning, promoting a more active learning classroom environment (Ragan, Jennings, Massey, & Doolittle, 2014; Weaver & Nison, 2005; Wurst, Smarkola, &

Gaffney, 2008). Conversely, students using laptops in class also experience more distraction and perform at lower levels of academic success compared to students not using laptops (Fried, 2008). Students describe using laptops to surf the web, watch movies, play games and check social media while in class (Lauricella & Kay, 2010).

Interestingly, using laptops in class affected more people than just the student with the laptop. Sana, Weston, & Cepeda (2013) discovered that students sitting near someone using a laptop performed worse on tests as compared to students without the distraction of the laptop. Studies attribute this lack of success to the distractions created by the technology (Hembrooke & Gay, 2003). Laptops are one of the oldest forms of modern technology used by college students, however, they are not the only distraction contemporary students face. Researchers are finding that a newer form of technology is also directly competing for a college student's attention. Mobile phones have become prolific throughout higher education and the following section examines how these personal technology devices are impacting students.

Mobile phones. Radio and television are examples of intellectual technologies, or technologies that stretch brain functions. Mobile phones are an example of networked technologies. Scholars classify network technologies as an extension of intellectual technologies (Misra, et. al., 2016). Interestingly, studies show networked technologies absorb other intellectual technologies (Carr, 2010). In this way, mobile phones have affected society arguably as much as any previous form of technological innovation.

Mobile phones provide vast arrays of information in the palm of the hand. Phones have taken the place of maps, watches, and television, just to name a few of the popular functions. These functions have led scholars to posit that mobile technologies create an *absent presence* (Gergen, 2002; Stone, 2007). The notion of *absent presence* is that a person is physically in one place, but because of technology, they are mentally elsewhere. This absent presence creates situations where mobile phone users are occupying two realities at once: a virtual reality and a present reality (Misra, et. al., 2016). Due to these dual realities and the tension to function between them, studies are showing that two primary implications are present: microsocial fragmentation (Gergen, 2003) and horizontal relationships (Gergen, 2002).

Microsocial fragmentation. Mobile phones allow the user to manage multiple social groups such as family, friends, and work colleagues, at one time. Proximity and communication challenges of the past are virtually eliminated, and users can connect with people in real time all around the globe. Users think about this unrestricted connection whether using the phone or not (Srivastava, 2005). These connections create tension in the brain and frequently subsume other brain functions, making it difficult for the individual to be present. One study showed that people in small groups checked their mobile devices every three to five minutes, even if it did not buzz or ring (Misra & Genevie, 2013). Along these same lines, numerous studies show an emerging phenomenon called “phantom vibration” where the users think their phone is vibrating in a pocket or bag, when it actually is not (Drouin, Kaiser, & Miller, 2012; Lin, Lin, Li, Huang, & Chen, 2013).

The phantom vibrations and constant impulses people feel to check phones creates a cognitive tension that challenges the present reality. This tension creates distraction and withdrawal from real-time, present relationships; this is frustrating to friends and acquaintances in proximity (Humphreys, 2005). This frustration and tension oftentimes fracture in-person interactions and relationships because distance relationships, conversations, and other concerns are salient (Turkle, 2012).

For college students, this microsocial fragmentation is challenging. As mentioned previously, students may become distracted in class by phones even if they do not buzz or ring. Furthermore, the virtual connections provided by burgeoning technologies may strain social relationships in class, on campus, or at events. Students may feel connected to many people, but long for the deeper, real interpersonal relationships (Gergen, 2002). This is an example of how horizontal relationships challenge vertical relationships. The next section discusses this shift from vertical relationship to horizontal relationship.

Horizontal relationships. The divided attention technology has ushered into society has created a societal shift from vertical relationships to more horizontal relationships (Misra, et. al, 2016). Superficial, shallow commitments that take relatively little to no effort or attention depict horizontal relationships. Conversely, vertical relationships are deeper and more meaningful. In order to strengthen vertical relationships time is required, along with commitment and many times some sacrifice (Gergen, 2002). Conversations in horizontal relationships are brief, simple and rarely require follow up. Some call these horizontal conversations sound bytes. Mobile phones and other technologies continue to encourage these types of conversations and relationships (Gergen, 2002; Turkle, 2012).

This societal shift towards horizontal relationships has strained basic tenets of compassion, empathy and deeper understanding in culture today (Immordino-Yang, et. al., 2009). The type of introspection and processing necessary for empathy and compassion to occur is typically slower and more involved. Oftentimes, vertical relationships produce this type of thought process that may take considerable amounts of time (Immordino-Yang, et. al., 2009).

College students with largely horizontal relationships may be less inclined to engage in serious discussions or challenging interpersonal relationships because they are conditioned for quick, short, shallow interactions (Gergen, 2003; Turkle, 2012). Even if students seek deeper understanding, distractions created by technology often inhibit or distract from meaningful engagements. If the mere visual presence of a cell phone is enough to distract and limit conversation (Przybylski & Weinstein, 2013), then the challenges students face with cultivating vertical relationships are great. These challenges for deep meaningful relationships may impact a student's confidence and create another distraction. The distractions created by technology whether through inner personal relationship struggles or the more overt visual distractions created by mobile phones or laptops arguably directly compete with a student's ability to learn.

It should be noted that laptops and mobile phones are just two forms of technology highlighted in this literature review. They were highlighted because throughout the literature, they are largely the most discussed forms of personal technology students' use in classes. The next section focuses on actual time on task, and how time spent utilizing technology leads to lower academic performance.

Time spent on technology. Recent studies attribute student's struggles in college with extended technology use (Edwards, 2015). One example of this is in the way college students allot time. Edwards (2015) found that time spent by college students using technology competes directly with time spent on academic pursuits, like reading, studying and researching. A study by Arum and Roska (2011) found that one third of college students spend less than six hours a week studying or performing other academic endeavors. Alternately, the same study revealed that two thirds of students spent six or more hours on non-academic tasks such as using technology or socializing each week.

The 2014 UCLA CIRP (Eagan et. al., 2014) reported that over a quarter of students surveyed spent more than six hours a week on social media or other forms of technology, including video games and Internet surfing. This percentage was the highest in the history of the longitudinal survey. Recent technology innovations have added another competitor to time management, and compared to previous generations of students, students today spend more time on technology and less on academic pursuits.

There is a significant relationship between student success and the amount of time a student spends using a laptop in class. Research indicates that college students use laptops in class for non-academic or off task purposes two-thirds of the time (Ragan, Jennings, Massey, & Doolittle, 2014). The longer a student spends using a laptop during class is directly related to lower levels of academic performance (Aguilar-Roca, Williams & O'Dowd, 2012; Fried, 2008; Grace-Martin & Gay, 2001; Hembrooke & Gay, 2003).

The same is true for broader technology use as well. There is a relationship between a student's grade point average and the amount of time a student spends on non-essential technology (Kraushaar & Novak, 2010). Examples of non-essential technology use are surfing the Internet, browsing social media, and texting or online chatting (Derbyshire, et. al., 2013). Additionally, students distracted by non-academic technology use, either personal or that of a classmate, may experience lower levels of academic performance (Kraushaar & Novak, 2010).

College students distracted by or utilizing non-academic technology at high levels are more likely than their peers to fall behind in school, which leads to lower levels of persistence (Armstrong, Phillips & Saling, 2000). Specifically, students spending higher amounts of time on the Internet or mobile phones have a lower self-confidence and score lower on emotional intelligence inventories when compared to peers who spend less time on the Internet and mobile phones (Beranuy, et. al., 2009). These same students also have lower retention rates when compared to peers using less non-academic technology (Beranuy, et. al., 2009). These lower retention rates may lead some students to suffer psychological issues. The next section will review some of the psychosocial issues students face.

Technology use and psychosocial issues. In addition to the strain technology use has on academic success, numerous studies are focusing on troubling psychosocial byproducts of extended technology use among college students. Moderate to severe levels of Internet Addiction may lead to a range of psychosocial issues in college-aged young adults (Derbyshire, et. al., 2013). For example, college students using technology more than their peers exhibit higher levels of stress (Dick, 2013; Kim, et. al., 2007; Pennebaker, et.al., 2001; Turner, et. al., 1995). Many students today are plugged into various forms of technology, and the stress associated with technology use and in more severe cases, technology addiction, is creating negative experiences such as loneliness and depression (Turel, 2015; Velezmoro, Lacefield, & Roberti, 2010; Wei, 2001).

Research is also discovering connections between higher levels of screen time associated with lower levels of psychological well-being. Psychological well-being is comprised of happiness, self-esteem and overall satisfaction measures (Twenge, Martin,

& Campbell, 2018). Students spending more time on technology and less time on non-technology activities such as sports or clubs, social interactions, and religious activity reported lower levels of psychological well-being (Twenge, Martin, & Campbell, 2018).

Researchers are finding links between stress, psychological well-being, and Internet addiction. As a student's Internet addiction increases, depression and stress scores increase significantly (Derbyshire, et. al., 2013). This relationship is troubling because students presenting symptoms of higher levels of stress are less likely to persist compared to students with lower stress levels (Krumrei-Mancuso, Newton, Kim, & Wilcox, 2013; Velezmoro, Lacefield, & Roberti, 2010). One body of literature linking technology to higher levels of stress and depression is the study of social media use and is discussed further in the following section.

Social media impacts. In 2011, over ninety percent of college students used Facebook, with fifty-eight percent using it multiple times a day (Dahlstrom, 2011). Extending the study to include other forms of social media (Twitter, Instagram, etc.), that number increased to nearly ninety-five percent (Dahlstrom, 2011). It is safe to say that college students, along with large portions of society, are using social media.

Interestingly, as students matriculate through college, it appears they may utilize social media at lower amounts. In 2015, college seniors were shown to spend less time on social media as compared to first-year students. In fact, as students moved from first-year students to second to third, each year was associated with lower levels of social media use (Junco, 2015).

Students often recognize their personal technology use is interfering with academics. Students who used Facebook regularly admitted that they studied less than peers who they perceived used Facebook less than them (Wentworth & Middleton, 2014). Seventy-nine percent of these students, however, felt that their social media use was not affecting academic performance (Wentworth & Middleton, 2014). This same study found a negative correlation between the time a student spent on social media and grades. The authors found that a student's self-report pertaining to technology use had little to no impact and was not accurate to the findings (Wentworth & Middleton, 2014).

There are conflicting bodies of literature discussing social media use and education. Between 2008 and 2010, researchers reported neutral or even positive effects of technology use in relation to academics. In 2009, a study found that Facebook use had no statistically significant impact on a student's grades (Pasek, More & Hargittai, 2009). Hargittai and Hsieh (2010) found similar results in that students using various forms of social media showed no difference in academic performance when compared to peers not using social media. Likewise, a study presented in the NASPA journal in 2008 presented a positive relationship between a student's grade and moderate amounts of Facebook use (Kolek, & Saunders, 2008).

The literature documents the negative impacts that technology use has on students quite well. The following section seeks to better explore how these negative impacts of technology use impact student success. Using theory to help illuminate these impacts is a critical step in a research project. The following section outlines and discusses the theories that influenced this study.

Relevant Theories

Two theories influenced the design of this study exploring the relationship between a student's addiction to technology and the Internet and academic performance as measured by grade point average (GPA). The two theories presented below are Rational Addiction Theory and Distraction-Conflict Theory.

The Rational Addiction Theory describes how an individual has an understanding that behaviors are, or may be, addictive, yet rationally chooses the behaviors anyway (Gruber & Koszegi, 2001). For this study, the Rational Addiction Theory presents even though college students might recognize that non-academic technology and Internet use are potentially hurting academic endeavors, the students, for example, still choose to spend time on social media rather than study.

The Distraction-Conflict Theory presents that distractions negatively affect learning and competence, particularly when an individual is experiencing challenging activities. A basic premise of Distraction Conflict is that the more difficult the task, the more impact distractions have (Sanders, 1981). For this study, the hypothesis is that students attending demanding, college classes or reading and studying challenging college content will experience lower academic achievement due to the use of technology or distractions that non-academic technologies present.

Rational Addiction Theory

Rational addiction theory is a standard modeling theory focusing on addictive behaviors. Rational addiction theory posits that addicts understand and recognize addictive behaviors, but rationally choose to continue with the behaviors because they value the addictive behavior over the potential negative costs of said behavior (Gruber & Koszegi, 2001). A primary tenet of rational addiction theory is that present-minded people have a likelihood of addiction as compared to future-minded people (Becker & Murphy, 1988). This is largely because present-minded individuals focus on the here and now, thus they are not concerned with how choices today impact tomorrow or the future (Becker & Murphy, 1988). Furthermore, the more addicted a person becomes, not only does the consumption of the product increase, but also the myopic view of the present grows with less forward thinking.

Another implication of the Rational Addiction Theory is that it takes a sudden or immediate cessation to stop the addictive behavior (Becker & Murphy, 1988). A common term for this is 'cold turkey.' Rational Addiction Theory says the stronger the addiction, the quicker or more abrupt rationally addicted people need to terminate the addiction. Conversely, weaker addictions may take more time to end. Many rationally addicted people claim to fail continually when attempting to wean off an addiction. However, many claim success with abrupt endings (Becker & Murphy, 1988).

As was discussed previously, the major tenets of rational addiction theory are indicative of college students' problematic technology use. Many students choose to spend time distracted on technology at the expense of educational success. Many times, these short-term choices to play video games or browse social media are present-minded, not often considering how the behaviors impact the future. The rise of contemporary technology on college campuses and the emerging addictive behaviors college students are exhibiting relating to technology use creates a complex issue that deserves the attention of higher education leaders, scholars and practitioners. Rational Addiction Theory partners nicely with another theory to help inform the relationship between Internet addiction and academic achievement. The next section explores Distraction Conflict theory and presents how this theory, along with Rational Addiction theory provide insights to this study.

Distraction-Conflict Theory

Zajonc’s Distraction-Conflict (DC) theory is a tenet of the broader Social Facilitation theory (Sanders, 1981). Distraction Conflict analyzes how individuals work with distractions. This theory surmises that when distractions are present, they create a physiological arousal in a person. Initially, distractions help an individual focus and perform better on easy, rudimentary tasks; however, as the tasks become more complex, the individual begins to struggle managing the distraction and the task at hand (Sanders, 1981). Distractions can be any stimuli, social or non-social that does not align with the task. The stimuli can be external or internal to the individual, created by the individual or another party. These distractions create an attentional conflict where a person must decide how to focus attention (Sanders, 1978).

Zajonc (1965) believed that people respond to situations largely in one of two ways. Dominant responses are responses that are used most often, thus the term dominates the hierarchy of responses. These dominant responses are oftentimes second nature, and because of the number of times an individual uses these responses, they are easily reproduced. Zajonc further described a second type of response. These responses are used, but much more sparingly by the individual. These responses are coined non-dominant responses. Zajonc concludes that when distractions happen, the physiological arousal increases the tendency to use a dominant response. The more complex the task, or the greater the distraction, the less likely that a non-dominant response is used (Zajonc, 1965).

To understand Distraction-Conflict Theory better, it is important to review three key components of the theory. These three components are social facilitation, cognitive load and working memory, and task complexity (Nicholson, Parboteeah, Nicholson, & Valacich, 2005). Each of the three plays an important role in Distraction-Conflict Theory and is presented more in depth in the following section.

Social facilitation. Social facilitation centers on how a person performs when encountered with another person. When a person focuses on a task and another person enters, this creates a physiological arousal and a distraction. This is also known as social facilitation. For some, these social distractions help complete the task, while for others, these social distractions can hinder performance (Nicholson, Parboteeah, Nicholson, & Valacich, 2005; Sanders, 1978). The social distractions create a cognitive load which impacts working memory and performance. Depending on the complexity of the task, a person might struggle to facilitate social distractions while attempting to complete the task. In this way, social facilitation closely relates to cognitive load, which is discussed in the next section.

Cognitive load and working memory. Cognitive psychologists describe cognitive load as a level of mental activity at any given time that imposes on the working memory of a person (Nicholson, Parboteeah, Nicholson, & Valacich, 2005; Sweller, 1994). Working memory, also known as short-term memory, is directly related to how quickly one processes information or thinks about things. Working memory is the temporary storage files of the brain. Cognitive load directly affects working memory. When too many distractions bombard a person, the cognitive load increases and taxes the working memory. When this happens, a person is oftentimes challenged with choosing a focus, which in the presence of more complex tasks, limits the ability to complete the task (Nicholson, Parboteeah, Nicholson, & Valacich, 2005).

Task complexity. The final component of the Distraction-Conflict Theory is task complexity. Task complexity is easily defined as the level of complexity or difficulty of the task at hand. This component is relative to the individual and is based on several factors including aptitude, experience with the task, and other internal and external factors present when the task is presented (Sweller, Van Merrienboer, & Paas, 1998). Task complexity relates to cognitive load in that the easier the task, the lower the cognitive load. Conversely, the more difficult the task, the greater the cognitive load.

Better understanding the three components of social facilitation, cognitive load and working memory, and task complexity helps one understand that a person's performance will vary greatly depending on these factors. In general, the more complex the task, the more a person will struggle when confronted with distraction (Nicholson, Parboteeah, Nicholson, & Valacich, 2005). In this study the assumption is that college lectures and academic work (reading, writing, and research) are complex tasks for many, thus distractions may cause a person to struggle.

As previously discussed, non-academic technology use creates a distraction. Studies are also indicating that technological distractions might challenge cognitive load and working memory more than other distractions, increasing the difficulty of highly complex tasks when confronted with non-task technology (Fockert, 2013). Because the human brain cannot multitask, these distractions will likely negatively affect performance.

Rational Addiction and Distraction-Conflict help describe struggles college students arguably face when presented with technology that competes for attention. In addition to the distraction technology presents to college students, recently higher education scholars and practitioners are witnessing a new phenomenon not previously seen in college. Studies are showing that a growing segment of college students are enrolling in college addicted to technology (Agarwal & Kar, 2015; Young, 1998). This addiction, like other addictions, has major implications on student success. The next section of the literature review analyzes the instruments created to research this growing addiction.

Internet Addiction and Problematic Internet Use Assessments

Technology use has steadily increased in society throughout the 21st century (Perrin & Duggan, 2015). Internet abuse is the country's fastest growing addiction, including both non-chemical and chemical addictions. This research was based on an ABC News study conducted with over 17,000 respondents (Holden, 2001). An additional study in 1999 found that over six million North Americans likely were addicted to the Internet (Yang, 2000). As mentioned previously, literature shows that college students spend more time on the Internet and utilizing other forms of technology today when compared to previous generations (Eagan et. al., 2014). With this increased technology use, researchers are finding relationships between extended, compulsive technological use and addictive behavior (Agarwal & Kar, 2015; Young, 1998).

Technology addiction is defined as a psychological dependence on Internet technology and is characterized by an increased investment of resources on technology related activities (Nalwa & Anand, 2003). Today, college students exhibit behavior connected to this newer addiction. A common characteristic of college students who exhibit Internet addiction tendencies is that students tend to be lonely and use online social networks to handle loneliness (Engelberg & Sjoberg, 2004). Additionally, studies show that male students are more vulnerable to Internet addiction as compared to female students (Kubey, Lavin & Barrows, 2001; Morahan-Martin & Schumacher, 2000). As previously discussed, students showing Internet addiction tendencies also tend to struggle academically.

Over the past twenty years, researchers have created assessments attempting to measure an individual's level of problematic Internet usage. This section will explore six assessments utilized in this exploration. Starting with the assessment used for this project, Young’s Internet Addiction Test, a brief summary of each instrument and associated validity testing is included. The assessments are discussed chronologically in relation to the year in which they were created.

Internet Addiction Test (IAT)

The Internet is one form of technology receiving extensive research as it relates to addiction. Dr. Kimberly Young created the Center for Internet Addiction at St. Bonaventure University in 1995. Shortly after, in 1998, she introduced the Internet Addiction Test (IAT). Young defined Internet addiction as “an impulse-control disorder which does not involve an intoxicant” (Young 1996, p.238)

The IAT is a tool that correlates time spent on Internet to addictive behaviors (Chang & Law, 2008; Faraci, Craparo, Messina, & Severino, 2013). Dr. Young and other researchers are finding that technology addiction is growing, particularly in college students today (Christakis et. al., 2011). Young modeled eight questions in the initial IAT after Pathological Gambling criteria outlined in DSM-III and IV (DSM-IV; American Psychiatric Association, 1994). Twelve questions were added later seeking a deeper understanding of dependent and nondependent Internet users making the IAT a twenty-question inventory (Widyanto, Griffiths & Brunsden, 2011). The initial studies using the IAT began to receive national publicity with results published in *The Wall Street Journal, The New York Times, and the London Times* (Young, 1998).

The IAT uses a six-point Likert scale and divides respondents into four categories. Respondents scoring between 0-30 points reflect normal Internet usage. Scores of 31-49 represent mild Internet addiction. Respondents scoring 50-79 represent moderate levels of Internet addiction and scoring 80-100 represents a severe dependence on the Internet (Young, 1998). Appendix A contains the questions for the IAT along with the scoring rubric and instructions.

Numerous studies tested the IAT and found the instrument valid and reliable. (McMurran & Widyanto, 2004; Widyanto, Griffiths & Brunsden, 2011). A factor analysis revealed strong internal consistency and concurrent validity with six factors: salience, neglecting work, neglecting social life, excessive use, lack of control, and anticipation (Widyanto, Griffiths & Brunsden, 2011). The most reliable of these six factors was salience.

The IAT was one of the first assessments created to assess Internet addiction. Because of this, it is one of the most popular and is still used by researchers. The IAT, however, is not the only instrument available. The following section will provide a cursory overview of five additional instruments created to analyze the Internet addiction phenomena. These were chosen to help provide perspective on the instruments available for this study.

Pathological Internet Use Scale

The Pathological Internet Use Scale was created by researchers Morahan-Martin and Schumacher (2000) to conduct research on Internet addiction. This study created the term "Pathological Internet Use" (PIU) instead of Internet addiction (Morahan-Martin & Schumacher, 2000). This specific study used thirteen questions and focused more on the behaviors of PIU. Coupled with the UCLA Loneliness scale, the study found that a little over eight percent of respondents experienced PIU. The Pathological Internet Use Scale has high levels of internal validity (Morahan-Martin & Schumacher, 2000) and posits that users scoring higher levels of PIU chose to have social interactions online instead of in person. Additionally, higher PIUs felt much more competent and comfortable in online social settings as compared to face-to-face interactions.

Generalized Problematic Internet Use Scale (GPIUS)

Using the Davis' (2001) Problematic Internet Use theory, the Generalized Problematic Internet Use Scale was created to conduct a study on undergraduate students at the University of Delaware (Caplan, 2002). Like the Pathological Internet Use Scale, Caplan (2002) administered the GPIUS with the UCLA Loneliness scale, along with three other psychometric measures. Three hundred and eighty six University of Delaware students took part in the research project. Only one finding was reliable and that was that shy students tended to use the Internet for socializing more than face-to-face contact.

Internet Addiction Scale (IAS)

The Internet Addiction Scale was developed and initially distributed in Canada in 2004 (Nichols & Nicki, 2004). Like the IAT, the IAS used the substance dependence criteria of *DSM-IV* in the creation of the 31-question inventory (American Psychiatric Association, 1994). Unlike the IAT, which had six factors prove reliable, the IAS only had one reliable factor, salience (Nichols & Nicki, 2004). Another concern was that compared to the other assessment inventories, the IAS only found one percent of respondents dependent to the Internet as compared to a thirteen percent average of other inventories (Nichols & Nicki, 2004).

Internet Addiction Tendency Scale

In 2004, researchers Song, Larose, Eastin and Lin studied the difference between process gratification and content gratification as it relates to the tendency to become addicted to the Internet (Song, Larose, Eastin, & Lin, 2004). Content gratification focused on an individual's pleasure from the material on the Internet, while process gratification focused on merely the practice of using the Internet. The researchers conducted the study at both the University of Michigan and Ohio University with 498 combined respondents. Researchers created the Internet Addiction Tendency Scale to conduct the study. Through factor analysis, the researchers found only one factor to be significant: Information Seeking. Furthermore, the factor of diversion, which the authors predicted as unrelated, was found to be significant (Song, Larose, Eastin, & Lin, 2004).

Internet Effect Scale (IES)

Two researchers created the Internet Effect Scale to conduct a study in Pakistan. The IES is included in this review of assessments for two reasons. The first is it is a more recent attempt at assessment as compared to the others and, secondly, it attempted to analyze both the positive and negative effects of Internet use (Suhail & Bargees, 2006).

The study found that all six factors pertaining to negative aspects of Internet use were weak or moderately correlated.

Additionally, the positive factors failed to show significance alone and only when paired with a negative factor was any significance achieved. Suhail & Bargees (2006) concluded that due to the smaller sample size, any relationship between positive and negative effects of Internet use could not be confirmed. Further, the only significance found, although weak, was with the negative effects leading the researchers to posit that time spent on the Internet resulted in users experiencing negative effects (Suhail & Bargees, 2006).

Each of these assessment tools provides different insights into Internet Addiction and/or Problematic Internet Usage. Often, researchers developed a tool for personal studies. Young's IAT is arguably the most popular and validated tool in the literature. The Internet and other technologies are growing more complex, and it is important for researchers to understand the context of the type of Internet use that is studied and utilize the appropriate instrument (Widyanto, Griffiths & Brunsden, 2011).

The Internet Addiction Test (IAT) is the most commonly utilized instrument to gauge Internet addiction. This study used the IAT to identify levels of Internet addiction. The next section of this literature review explores the divide in terminology between Internet addiction and Problematic Internet Use.

Internet Addiction or Problematic Internet Use

Scholars are divided on what to call the phenomenon of individuals struggling with time spent on the Internet and other forms of technology. Numerous scholars call this "Internet addiction" (Young, 1998; Young, 1996; Griffith, 1998; Nichols & Nicki, 2004; Song, Larose Eastin, & Lin, 2004; Simkova & Cincera, 2004). A working definition for Internet Addiction is a psychological dependence on the Internet that impacts the individual (Young, 1998). However, in the research community, dissention surrounds the term Internet addiction.

Although DSM-V has added Internet Gaming Disorder, traditionally the clinical community points back to DSM-IV, which outlines addictions pertaining to substances. Griffiths (2000) contends that a person using the Internet is not addicted to the Internet itself but is using it as a medium to achieve other addictive behaviors such as online gambling (gambling addiction), or online pornography (sexual addiction). For Griffiths and other researchers, (Caplan, 2002; Davis, Flett, & Besser, 2002; Erickson, 2008), the Internet is a conduit feeding other pathological behavior. These researchers use the term Problematic Internet Use (PIU) rather than Internet Addiction. This project will use Internet Addiction because it aligns with Young's IAT (1998), unless discussing studies where instruments are specifically tailored to the term Problematic Internet Use.

Conclusion

Over the past two decades, technology has exploded onto college campuses. Technology provides education to historically underserved populations of students. Additionally, technology advancements allow educators to meet a variety of learning preferences. The value of technology in education is not difficult to observe. However, a concern is that along with positive aspects to technology use in education, negative implications are also presenting.

As discussed, researchers are linking technology use to numerous barriers with college student success, leading to lower student persistence and success. Educators and decision makers in higher education must be aware of these factors and make decisions accordingly to help institutions move forward in a world entrenched in technology and its use. It is becoming evident that technology is significantly affecting college students today.

The question that is arguably more pertinent than ever is how is technology affecting students? This study provided an examination of how technology use and in some cases Internet addiction impacts college students using the IAT to gauge Internet use and addiction, and explored relationships between the IAT score, academic achievement, and student demographics. This study may offer initial insights to higher education decision makers, and provide a better understanding of the implications of technology use among contemporary college students. This understanding may help identify students who are addicted to the Internet and potentially negatively impacted by individual technology use.

CHAPTER III

METHODOLOGY

Research Context

Individual technology use is increasing rapidly among college students with students reporting that not only they use technology at increasing levels, but they are becoming more reliant on forms of electronic technology to study and stay connected with peers (Derbyshire, et. al., 2013; Kessler, 2011). With technology prevalent throughout higher education, researchers are questioning how the increased technology exposure and use is impacting college students.

This chapter discusses the research study's design, which includes the research perspective, purpose statement, research questions and hypothesis. Research population and intended sampling are also discussed, followed by presentation of the study's methodology and instrument. Finally, data collection procedures, data analysis, limitations, and delimitations of the study are provided.

Research Design

Research Perspective

Crotty (1998) defines epistemology as "how we know what we know" (p.8). Meaning existing independently from human conscience is a primary tenant of objectivism (Crotty, 1998). Objectivists actively analyze and look for facts when seeking truth (Crotty, 1998). Although seeking objective truth, post-positivism suggests that knowledge depends on human interpretation and experiences, making it difficult to find an absolute truth (Creswell, 2014). Post-positivism is centered on seeking understanding for regular, observed phenomena (Crotty, 1998). Based on this, the researcher positioned this study using an objectivist epistemology with a post-positive theoretical perspective.

Along with the objectivism and post-positive alignment, this study used a quantitative design and explored the relationship between the Internet Addiction Test scores and student success as measured by grade point average. Furthermore, the study analyzed if the IAT score was predictive of grade point average, and sought to find if there were differences between reported IAT scores and student demographics including sex, research site, race and student classification.

Purpose Statement

The purpose of this quantitative study was to analyze the relationship of the Internet Addiction Test (IAT) score and academic performance and identify difference between student demographic variables and IAT scores. This study used Young's (1998) Internet Addiction Test (IAT). The IAT score was used to determine a student's addiction to the Internet. A student's academic performance was measured by grade point average. A student's demographics included sex, research site, race, and student classification.

Research Questions and Hypothesis

Informed by rational addiction theory and distraction conflict theory discussed in Chapter Two, this study tested the relationship between a student's IAT score and grade point average, and analyzed if there was an influence between traditional college students' IAT scores and grade point averages was analyzed. Additionally, the study examined if there were any differences between the demographic variables of sex, research site, race and student classification and IAT score. This section provides detail of the research questions and research hypotheses for the study.

Research Questions. Six research questions guide this study. The first question was:

RQ1: *"Is there a relationship between a student's Internet Addiction Test (IAT) score and grade point average?"*

RQ1: H0/Null hypothesis: There is not a significant relationship between IAT score and grade point average.

RQ1: Ha/Alternate hypothesis: Students' scores on the IAT are significantly related with grade point average.

Based on the theoretical framework for this study, along with the literature presented in Chapter Two, it was anticipated that the null hypothesis for this question was rejected and there would be a significant relationship between IAT score and grade point average. Moreover, it was anticipated that this relationship was negative, meaning a higher IAT score related with a lower grade point average.

The second research question was:

RQ2: "*Is there a mean difference among sex and IAT score?"*

RQ2: Ho/Null hypothesis: There is no significant difference of means of IAT score and sex.

Ha/Alternate hypothesis: There is a significant difference of mean of IAT score and sex.

Based on the IAT literature previously discussed in Chapter Two, it was anticipated that the null hypothesis for this question would be rejected and there will be a significant difference in the means of IAT and sex.

The third research question was:

RQ3: "*Is there a mean difference among research site and IAT score?*"

RQ3: Ho/Null hypothesis: There is no significant difference of means of IAT score and research site.

Ha/Alternate hypothesis: There is a significant difference of mean of IAT score and research site.

Based on the IAT literature it is anticipated that the null hypothesis for this question would be confirmed and there would not be a significant difference in the means of IAT and research site.

The fourth research question was:

RQ4: "*Is there a mean difference among race and IAT score?*"

RQ4: Ho/Null hypothesis: There is no significant difference of means of IAT score and race.

Ha/Alternate hypothesis: There is a significant difference of mean IAT score and race.

Though the literature pertaining to race and Internet addiction is extremely limited, based on the student success literature previously discussed in Chapter Two, it was anticipated that the null hypothesis for this question would be rejected and there would be a significant difference in the means of IAT score and race.

The fifth research question was:

RQ5: "*Is there a mean difference among classification and IAT score?*"

RQ5: Ho/Null hypothesis: There is no significant difference of means of IAT score and student classification.

Ha/Alternate hypothesis: There is a significant difference of mean of IAT score and student classification.

Based on the IAT literature previously discussed in Chapter Two, it was anticipated that the null hypothesis for this question would be rejected and there would be a significant difference in the means of IAT and student classification. The literature presents that upper division students tend to use the internet for nonacademic use less than lower division students.

Research Population, Sampling, and Data Collection

Population

Traditional aged college students commonly categorized as students between the ages of 18-25 years of age are a subgroup of students attending higher education institutions. As discussed in Chapters One and Two, this same age group, called digital natives by some scholars, has grown up in a world surrounded by different forms of technology. For this reason, the population of the study was traditionally aged (ages 18-25) college students attending college in Oklahoma during the spring 2019 semester.

Traditional aged students from both public and private institutions in Oklahoma participated in this study. The institutions selected for this study were a public, four-year research institution with more than 20,000 students, a private, four-year, liberal arts institution with more than 3,000 students, and a religiously affiliated, private, four-year liberal arts institution with more than 2,000 students. These schools were selected to create a broad sample from the region of traditional college students from both public and private institutions in a regional setting. One of the variables in the study is research site, thus the selection of both public and private institutions.

Sampling

As previously outlined, this study used convenience sampling within the population requirements. Convenience sampling is a non-probability sampling method (Gay, et. al., 2012). Because the number of all traditional, public and private college students across the United States is large and may differ regionally, the researcher decided to focus the study on a regional selection of schools, making convenience sampling the method selected for the study. Convenience sampled participants were participants who were available at the time of the study, were willing to participate in the study, were accessible, and who met the criteria of the study in relation to the population parameters (Gay, et. al., 2012).

The researcher worked with the Institutional Research Board at each site to collect email lists of students 18-25 years of age. Emails were crafted for each participating institution and sent to each institution separately. However, the text of the emails was identical regardless of institution. All convenience sampled participants received an email with a link to the Qualtrics survey in the spring of 2019. Students were informed that the study was voluntary and were asked to electronically sign an IRB-approved informed consent form prior to completing the questionnaire by clicking on a radio button at the bottom of the consent form (Appendix B).

The questionnaire (IAT) included twenty questions focusing on an individual's Internet usage. Students self-reported their cumulative grade point average. A discussion on self-reporting GPA is included in Chapter Two. In addition, biographical information questions including sex, research site, race, and student classification were included in the instrument. Finally, there were three internal validity questions. The instrument is included in its entirety in Appendix A.

Methodology and Instrument

Methodology

This study utilized a quasi-experimental, cross-sectional, quantitative design. A cross-sectional design analyzes data from a population or representative sample of a population at a given point in time (Creswell, 2014). Data were collected through a web-based survey that was disseminated to student email addresses. The data were collected and stored in a password protected account. Only the primary researcher, his advisor, and the OSU IRB (if requested) have access to the data.

Young's (2008) IAT scoring metric allotted a score of 0-100 to each respondent that placed them in a range from normal Internet use to severe dependence on the Internet (100 total points). SPSS version 24 was utilized to examine, first, if there was a relationship between the student IAT score and GPA, second to study if the IAT was predictive of GPA, and finally, compared differences of the demographic means and the IAT scores. A Pearson correlation determined if a student's IAT score and grade point average were related, an OLS test (linear regression) determined if the score on the IAT predicted grade point average, and an ANOVA identified differences of means between the biographical variables and a student's IAT score.

Instrument

This study used Young's Internet Addiction Test (IAT); the IAT was created by Dr. Kimberly Young at St. Bonaventure University in 1998 (Young, 1998). Dr. Young created the IAT to assist with the intake of clients seeking support from the Center for

Internet Addiction. From 1998 to the present, the IAT was commonly used by scholars and counselors to help gauge an individual's problematic Internet use. The IAT has been tested and validated throughout the decades (Faraci, Craparo, Messina, & Severino, 2013). The following section discusses the IAT and its validity in more detail.

Dr. Young sought to create a tool to measure the time spent on the Internet and any relationship to addictive behavior. Young was working with clients at the St. Bonaventure Center for Internet Addiction and witnessed them experiencing major issues with time spent on the Internet. Young needed a tool to use at intake appointments (Chang & Law, 2008; Faraci, Craparo, Messina, & Severino, 2013).

The IAT is comprised of twenty questions, each using a six-point Likert scale. The first eight questions are modeled after pathological gambling criteria outlined in DSM-IV which was the version available at the time (DSM-IV; American Psychiatric Association, 1994). Young added twelve additional questions to help provide better understanding of the types of dependencies clients had regarding Internet use (Widyanto, Griffiths, & Brunsden, 2011).

Some sample IAT questions taken from the questionnaire are:

1. How often do you find that you stay online longer than you intended?

2. How often do you neglect household chores to spend more time online?

3. How often do you prefer the excitement of the Internet to intimacy with your partner?

4. How often do you form new relationships with fellow online users?

5. How often do others in your life complain to you about the amount of time you spend on-line?

The results of the IAT are divided into four categories. Respondents scoring 80 to 100 are identified as severely dependent on the Internet. Moderate levels of Internet addiction are scored ranging from 50 to 79. Scores of 31 to 49 are classified as mildly addicted to the Internet, and scores of 0 to 30 are normal Internet users (Young, 1998). For the purpose of this study the raw numerical score was used. See Appendix A for the complete list of IAT questions, accompanied by instructions, and scoring rubric.

Internet Addiction Test Validity. Arguably the first generally accepted test to measure Internet addiction, the IAT receives much scrutiny from researchers and has withstood numerous tests of validity and reliability. Many tests have shown the IAT to have high face value validity, but Wiyanto, Griffiths and Brunsden (2011) desired to run a psychometric test on the properties of the IAT. They conducted a study of both the IAT and the Internet-Related Problem Scale. The results for the IAT are discussed in this section.

In the Wiyanto, Griffiths and Brunsden (2011) psychometric study of the IAT, a factor analysis produced the following:

> Bartlett's test of sphericity indicated a chi-square value of 2207.8 ($p < 0.0001$), while a Kaiser-Meyer-Olkin measure of sampling adequacy indicated a value of 0.92. When a basic scree test and eigenvalue >1.0 criteria were used, three factors were generated from the IAT. These three factors, which were rotated to position of maximum orthogonality in six iterations, explained 56.3% of the variance (Wiyanto, Griffiths & Brunsden, 2011, pg. 143).

The three factors in the study were: Factor One, measuring psychological and emotional conflict and it accounted for 42.7% of the variance. Factor One also produced the highest Chronbach's alpha ($\alpha = 0.93$), which assumed high reliability. Factor Two measured time management conflicts and accounted for 8% of the variance, also with a high Cronbach's alpha score ($\alpha = 0.86$). Factor Three measured salience in terms of mood modification and accounted for 5.6% of the variance. Like the other two factors, high reliability is assumed with a high Cronbach's' alpha score ($\alpha = 0.86$). Additionally, each of these three factors showed strong internal consistency (Wiyanto, Griffiths & Brunsden, 2011).

The Wiyanto, Griffiths and Brunsden (2011) study also ran correlations between variables with age and frequency of Internet use showing significant correlations. Age is significantly correlated to time management issues (time-management issues, $r= 0.18$; $p < 0.01$), and frequency of Internet use is significant to time management issues and salience (time-management issues, $r= 0.26$, $p < 0.01$; salience in terms of mood modification, $r= 0.18$; $p < 0.05$) (Wiyanto, Griffiths & Brunsden, 2011, pg. 145-146).

Overall, the Wiyanto, Griffiths and Brunsden (2011) psychometric study found that time spent on the Internet was positively correlated with the IAT score, which suggests that the more time a user spends on the Internet, the higher likelihood of Internet addiction. The study also found that males tended to score much higher than females on the IAT and experienced higher levels of Internet addiction (Wiyanto, Griffiths & Brunsden, 2011). In addition to this study, the following studies produced similar results focusing on validity and reliability.

Widyanto & McMurran (2004) explored the psychometric properties of the IAT. This study used factor analysis to study the six primary factors of the IAT. The six factors examined were lack of control, excessive Internet use, salience, putting off work, neglecting social life and lack of self-control. The study found good internal consistency and validity. The study used a Pearson's correlation and found that all six factors were significantly correlated with ranges from $r = 0.62$ to $r = 0.226$, $p<.05$, in the two tailed test. The two strongest factors in the study were excessive use (Cronbach's $\alpha = 0.77$) and salience (Cronbach's α *o= 0.82).* The study concluded that the IAT was a reliable instrument and could be used for studying Internet addiction.

Pawlikowski, Altstötter-Gleich, & Brand (2013) studied the validation and psychometric properties of a short version of Young's Internet Addiction Test. The study addressed the factorial structure of the IAT. Using factor analysis to assess the IAT, the study found that the IAT has sound psychometric properties and the key elements and factors are valid and reliable with a Cronbach's α of .897. Based on this study, the researchers believe that the IAT is useful for gauging Internet Addiction.

Jelenchick, Becker, and Moreno (2012) assessed the psychometric properties of the Internet Addiction Test (IAT) as it relates to U.S. college students. This study used exploratory factor analysis to study the IAT along with 215 college students. Eighty-eight percent of the respondents tested as "average Internet users." Twelve percent tested as "problematic Internet users." The study found significance with Internet addiction in two factors: dependent use and excessive use. Dependent use was classified as social withdraw or awkwardness due to a preoccupation with the Internet and a Cronbach's $\alpha = 0.91$. Factor two, excessive use, was classified as loss of control or overuse of the

Internet with a Cronbach's α = 0.83. Additionally, the researchers claimed that the IAT instrument is valid, reliable and could be used to study Internet addiction in U.S. college students.

Frangos, Frangos, & Sotiropoulos (2012) conducted a study on the reliability of Young's Internet Addiction Test. This study was a meta-analysis of twenty studies with over 6,800 respondents using the IAT. Using the Cronbach's values in each study, the researchers found that the overall Cronbach's α = .889 and that the IAT is a valid and reliable instrument.

Each of these studies has provided support for validity and reliability of Young's Internet Addiction Test. Currently, the IAT is one of the most commonly used instruments for researchers studying Internet addiction. The IAT, however, is not immune from critique. The following section explores the critiques of the IAT.

IAT Critique. The IAT has received criticism in two main areas. The first area of criticism is that of self-reporting. Beard and Wolf (2001) questioned validity of the instrument when so many of the questions are based on the assumed objectivity of the respondent through self-reporting. Additionally, Beard and Wolf (2001) expressed concerns regarding the use of Pathological Gambling criteria used to model the first eight questions. A question was posed as to whether these criteria were the best choice for gauging Internet addiction.

Although these critiques raise concerns, the studies outlined previously (Frangos, Frangos, & Sotiropoulos, 2012; Wiyanto, Griffiths & Brunsden, 2011) suggest that the method of self-reporting does not influence the validity of the results. These studies demonstrate the IAT is a significant and reliable instrument for gauging Internet addiction. Each of the studies outlined above concluded that the IAT is a predictor of Internet addiction. It has stood the test of time and is still used today, twenty years later.

Variables and Codes

The following variables were used for the study; Sex, Research Site, Race, Student Classification, IAT score, and GPA. Research question number one explored the relationship between IAT score and grade point average. For research questions number two through five, the independent predictor variables of sex, research site, race, and student classification were each tested with the dependent variable of IAT score.

1. Sex: Sex was coded as a nominal variable with Female coded as “0”, Male coded as “1”, and No Answer coded as “2”.

2. Race: Race was coded as a nominal variable. There were nine subcategories in this variable. No Answer was coded as “1”, American Indian was coded as “2”, Black/African American was coded as “3”, Hispanic was coded as “4”, Asian was coded as “5”, Two or More races was coded as “6”, Other was coded as “7”, Unknown was coded as “8”, and White was coded as “9”. For the comparison of means race was categorized as “White/Non-White”. This coding along with the other codes are in Appendix D.

3. Internet Addiction Test score was a continuous variable. The IAT scores respondents from 0-100 with 0 – normal use and 100 – severely dependent on the Internet (Young, 1998).

4. Grade Point Average was a continuous variable. Because a linear regression was used for this study, the actual grade point average, rounded to the nearest hundredth was used.

5. Survey Site was a nominal variable. Each institution was coded 1, 2, 3. The institutions were recoded into public and private, (1 and 2), for the comparison of means in research question three. The codes were entered in the code book in Appendix D.

6. Classification was a nominal variable. There are four subcategories in this variable. 1st year was coded as 1, 2nd year was coded as 2, 3rd year was coded as 3, 4th year or more was coded as 4. The classifications were recoded into two nominal variables, underclass (1) and upperclass (2) for the comparison of means and are noted in the codebook in Appendix D.

Data Collection and Procedures

After final approval of the proposal by the Ph.D. student's committee, an application was sent to the Institutional Review Board at Oklahoma State University as well as to the IRBs at the two additional institutions where data were collected. The three institutions have pseudonyms Institution 1, Institution 2, and Institution 3. Before data were collected, all institutions provided IRB approval for the study (Appendix E). All respondents completed the Internet Addiction Test (IAT) online using the link provided to the Qualtrics questionnaire. Data collection was scheduled for a period of 45 and not exceeding 60 days following receipt of IRB approvals in the spring of 2019. The software program, Qualtrics, which is supported by Oklahoma State University was used to create, disseminate the instrument, and collect the data for this survey. Qualtrics is a database program utilized for collecting and analyzing data. The following section further describes the data collection methods and procedures more thoroughly.

Data Collection

Upon approval by the IRBs at all institutions, an email with the electronic Internet Addiction Test (IAT) form and supplemental questions was sent to each student in the population via an institution email address. When students clicked on the link and prior to entering the survey and taking the IAT, students were presented with a cover letter that contained the consent statement and an overview of the study's purpose statement. Students clicked on an "I Consent" icon which served as an electronic signature to participate in the study. Students who did not wish to complete the survey and clicked the "I do not consent" link were directed to a thank you page and did not complete the survey. Appendix B has a copy of the cover letter and consent statement.

After agreeing to the statement of consent, students read the instructions for the IAT. The instructions are as follows:

> "The questionnaire consists of 20 statements. After reading each statement carefully, based upon the 6-point Likert scale, please select the response 0, 1, 2, 3, 4 or 5 which best describes you. If two choices seem to apply equally well, circle the choice that best represents how you are most of the time during the past month. Be sure to read all the statements carefully before making your choice. The statements refer to offline situations or actions unless otherwise specified. In addition, you will be asked basic demographic questions and a question regarding the technology you use in class."

The survey should have taken each respondent five to ten minutes to complete. Two follow up emails were sent to the students who did not respond within two week increments (a total of three emails). No incentives were provided for this study. Respondent data were confidential and limited personally identifying information was collected by the researcher. Only the researcher, his advisor and the OSU IRB (upon request) have access to the data.

The surveys were completed online using Qualtrics software and asked for limited identifying information including basic demographics of self-reported grade point average, sex, race, year in school (classification), and research site. After the data were collected the variables were recoded in the working data set as outlined previously. The code book in Appendix D contains the codes for this study.

Survey data were kept in the password-protected account of the primary investigator (PI), and the data to be used in subsequent analyses were downloaded only to the password-protected computer of the PI. Only the PI, advisor and IRB has access to the completed survey data. The principal risks in this study are those associated with a breach of confidentiality concerning the respondent's involvement in the research.

Data Analysis

The following quantitative statistical measures were used to analyze the data. First, the data collected were analyzed to ensure that there was not any corrupted or incomplete data sets. This was done by importing the data collected in Qualtrics into IBM's Statistical Package for Social Sciences program version 24 (SPSS). The completed surveys were sorted in the database and all incomplete data sets were removed. Furthermore, any dataset not answering at least two of the three internal validity check questions correctly was discarded.

Once the data set was validated and complete, all data analysis was conducted using IBM's SPSS version 24. A descriptive analysis, Pearson's *r* analysis, linear regression analysis, and analysis of variance was conducted for this study. The following sections describe this process of analysis.

Descriptive. The descriptive analysis provides an overview of the sample of the population that completed the study. Descriptive statistics analyzed sex, research site, race, student classification, grade point average, IAT score. The descriptive statistics include number of participants, percentages, and means and were included in tables and graphs to provide a quick visual representation of the data sampled.

Correlation. Next, a Pearson correlation was used to measure the strength of relationship, if any, between the variables. Pearson *r* provided an estimate for both the direction and the strength of a linear relationship (Gay, et. al., 2012). The Pearson *r* range is +1.0 to -1.0. A result of 0.00 results from two variables that are independent from each other, or that do not have a linear relationship. If the result is a negative integer, then the relationship is negative. Conversely, a positive integer is the result of a positive relationship (Lomax & Hahs-Vaughn, 2012). For example, in this study one hypothesis was that the higher a student scores on the IAT the lower the grade point average. In this case the Pearson *r* score would be a negative integer, showing a negative relationship between IAT score and grade point average.

Regression. The next step of analysis for this study used an OLS analysis (linear regression) to test whether a student's IAT score significantly influenced grade point average. The predictor variable IAT score was tested with the dependent variable of grade point average. The purpose of a linear regression was to test the influence of the predictor variable with the dependent variable, in this case, was there a significant influence between a student's IAT score and academic success as measured by grade point average.

A simple linear regression has four important assumptions dealing with variables and residuals that were tested (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012). The first assumption is that the relationship between dependent and independent variables needs to be linear. For this study a scatter plot was used to test the linear nature of the variables. Using scatter plots may also easily depict outliers in the study (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012). This was important because regressions can be conscious of outlying variables.

A second assumption is that the residuals require a normal distribution or the assumption of normality. The residuals were plotted along a normal probability plot in SPSS. Also, a histogram was created to test normality (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012).

The third assumption for OLS is that autocorrelation is not present or is very minimal (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012). If the residuals are not independent from each other, autocorrelation may occur. To test for autocorrelation, a scatterplot was used along with the Durbin-Watson test. The Durbin-Watson test analyzed the HO to see if the residuals were linearly correlated (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012).

A final assumption of OLS is constant variance. Constant variance looks for the variance of error terms to be constant. Additionally, the mean must equal zero. A scatterplot was used to test for variance in this study (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012).

After the assumptions were addressed, a linear regression was used. The linear regression assisted the researcher in better understanding what influence the predictor variable had, if any on the dependent variable (Gay et. al., 2012; Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012). A linear regression was suitable for this study because it highlighted influence between variables that show significance. The linear regression helped provide a better understanding of whether the predictor variable (IAT Score) predicted grade point average (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012).

Analysis of Variance (ANOVA). An analysis of variance was used to determine if there was a significant difference between two or more groups (Gay et. al., 2012). ANOVA was used on research questions two through five. For this study, a one-way ANOVA was used to explore any significant differences between the independent variables (sex, research site, race, and student classification) on the dependent variable (IAT score).

Prior to analyzing with ANOVA, assumptions were tested. The assumptions were: the Independent variable was categorical or discreet, the dependent variable was continuous, the dependent variable was normally distributed, and the populations had equal variance. Refer to Appendix F for a table addressing these assumptions. The discussion for the assumptions was also included in the presentation of the data with corresponding research questions in Chapter Four. Additionally, for the ANOVA analysis each independent variable had two categories: Sex – Female, Male;

Classification – Underclass (1^{st} and 2^{nd} year), Upperclass (3^{rd}, 4^{th}, 5^{th} year); Ethnicity – White, Non-White; Research site – Public, Private.

Limitations and Delimitations

Research, in its very nature, is conducted with a specific focus and with specific variables and focused parameters. This section discusses and accounts for the limitations and delimitations in this study.

Limitations

This study, like other research studies, has limitations. One such limitation was the type of technology a student had and used. Students have a variety of technology devices at their disposal and the number of devices likely varied among respondents with some having and using many devices, whereas others may only have and use one or two. While the number of devices may or may not have an impact on student success, this study was more concerned with the IAT score, and the literature is not clear on any relationships between number of devices and IAT score.

Another limitation of this study was socioeconomic status. Socioeconomic status may inhibit a student's ability to have technology. A larger sample size and choosing a more regional population was an attempt to control for socioeconomic differences. An additional limitation acknowledged in this study was how competent a student was with individual technologies. Some students are highly competent with various forms of personal technologies while others are not. For this study, the level of competence was not studied, rather the links between IAT score and grade point average, along with other student demographics and IAT score was researched.

Another limitation was a smaller sample size. Even with collecting data from three institutions, the N was likely to be under 1,000, making it more difficult to generalize the findings within the three institutions. However, it was believed that this study will begin to pave the way for future studies seeking to find relationships between technology use and student success. Because the body of literature is still shallow on the topic of college students and personal technology use and any influences on student success, this study will hopefully help lay some groundwork for future research.

Since research on Internet addiction and college student achievement is limited, finding an instrument for this study was challenging. As discussed previously, the IAT was selected based on the literature showing it as one of the most utilized and long standing instruments utilized. However, Young's (1998) intent when creating the IAT was as an intake form for counseling clients. This population differs from traditionally aged college students and the IAT may not be a 'perfect fit' to analyze students' Internet addiction and use. Furthermore, technology has changed drastically since the inception of the IAT. The proliferation of social media, smartphones, and apps make it difficult to analyze what specifically distracts or challenges college students' attention, and the IAT strongly relies on time spent on the internet to assess addiction – a relationship which may not be as simple as suggested by the design as the IAT. To date the IAT is as good an instrument as is available, as discussed previously in Chapter Two, but numerous limitations to use of the instrument are acknowledged.

A final limitation is the assumption of autocorrelation was not met prior to analyzing the data using a linear regression. The autocorrelation assumption violation occurs when the residuals appear to be autocorrelated with each other or may be influenced with other residuals (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012). Failure to meet the autocorrelation assumption is a liability for this study because the significance found in the regression may not be as strong or the results may not be significant at all due to the possibility of autocorrelation (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012). While the other three assumptions for regression were met, the findings of the regression portion of the analysis should be interpreted with caution, noting this failed assumption.

Delimitations

As mentioned, every study has parameters and that was the case for this study. This section outlines the choices made by the researcher regarding the boundaries for the study. One delimitation for this study was that the sample group chosen was traditionally aged college students. This sample excluded some college students, more specifically, those older than 25 years of age and under 18 years of age. This was intentionally done to help focus the research on a generation of traditional students at similar developmental stages experiencing common technological advances while in higher education. As previously discussed, some call these students *digital natives.*

Studying students only in the Oklahoma geographic region was also a delimitation. As was discussed in the limitations section, researching a regional population was an attempt to account for broad socioeconomic differences that might present using a national population. To account for this delimitation, the researcher chose more than one institution along with different types and sizes of institutions in Oklahoma. This was done to achieve a larger, more diverse population of private and public, traditionally aged college students in the region.

Another delimitation for this study is the choice to conduct the study using an online form and email to disseminate the form. The choice to use the online process comes with the advantage of a lower cost to produce, faster data gathering, a larger population that can be sampled, and a greater level of anonymity because the respondent does not have to be present to participate. However, some detriments to the online surveying approach are that students will need access to technology to complete the survey. Furthermore, respondents will not be able to ask clarifying questions in person while completing the instrument. Participants were given the name of the researcher in the initial email, and encouraged to ask any questions via email.

As discussed previously, self-reporting was used in this study in both grade point average, but also in completing the Internet Addiction Test. Self-reporting may lend itself to differing issues such as social desirability and memory issues pertaining to the amount of time spent on the Internet. As discussed even with self-reporting, the literature shows the IAT, which is a self-reported instrument, is a valid instrument in measuring Internet issues (Wiyanto, Griffiths & Brunsden, 2011; Young 1998; Young, 2008). Furthermore, the literature discusses how student's self-reported grade point averages, are as valid an indicator of success as actual grade point average (Baird, 1976; Cole & Gonyea, 2010; Schwartz & Beaver, 2014; Sticca, et. al., 2017; Stone, et. al., 1999; Talento-Miller & Peyton, 2006).

A final delimitation was the choice to use convenience sampling in a regional setting. For this study, respondents were from a sample of three institutions in a region. One large, public, four-year, tier one institution and two regional, private, four-year institutions. Additionally, respondents voluntarily self-selected to the study, making higher response rates potentially difficult and making the results less generalizable. Convenience sampling also allowed for a greater chance of a sampling error because the sample could underrepresent or over represent the larger population. The descriptive statistics will help provide a general understanding of whether the population sampled is representative of the larger population by comparing the study results with the published demographics of the institutions used in the study (Table 4.1 and 4.2). Furthermore, a larger N will also attempt to combat issues created by convenience sampling.

The list of limitations and delimitations is not exhaustive. As mentioned, the body of literature pertaining to college students and the Internet Addiction Test is relatively limited, so even with these limitations, it is believed that this study will have value to literature, practice, and future research that is analyzing the topic of technology in higher education.

Conclusion

This study extended the body of literature intending to assist with a better understanding of the relationship between a student's IAT score and grade point average. The study also explored how IAT scores related to the demographics of sex, research site, race, and student classification. As technology innovations continue to rapidly increase, it is imperative that educators understand the relationship between technology and college student success. This study attempted to provide findings to assist in this discussion.

CHAPTER IV

ANALYSIS OF DATA

Chapter Overview

Chapter Four continues the discussion introduced in Chapter Three pertaining to the methodology and data collection of the study. The purpose of this quantitative study was to first analyze the relationship of the Internet Addiction Test (IAT) and academic performance, then study what influence the IAT score has on academic performance, and finally analyze if there is a difference between student demographic variables and IAT scores. This study used Young's (1998) Internet Addiction Test (IAT). The IAT measured the level of a student's addiction to the Internet. A student's academic performance was measured by grade point average. A student's demographics included sex, research site, race and student classification.

This chapter is divided into three primary sections. First, a review of the research questions is presented along with the accompanying hypotheses. Additionally, in this first section, the specific statistical analysis utilized for each question is offered. Next, a description and overview of the respondents in the study are presented. Finally, the results from the data analyses are presented. Chapter Four is a bridge to the final chapter containing more robust discussion of the study findings, along with recommendations for future research.

Research Questions and Hypotheses

As previously discussed, this study was guided by five research questions and hypotheses. These questions first sought to find if a student's score on the Internet Addiction Test (IAT) was related to a student's grade point average, and if the IAT score was predictive of success in college as measured by grade point average. Research questions two through five sought to better understand if there was a mean difference of IAT scores in the population between the variables of sex, research site, race, and student classification. The following section outlines both the research questions, accompanying directional and null hypotheses, and the specific statistical analysis utilized for each question. For additional discussion on the hypothesis anticipations, refer to Chapter Three.

RQ1: "Is there a relationship between a student's Internet Addiction Test (IAT) score and grade point average?"

RQ1: H0/Null hypothesis: There is not a significant relationship between IAT score and grade point average.

RQ1: Ha/Alternate hypothesis: Students' scores on the IAT are significantly related to grade point average.

RQ2: "Is there a mean difference among sex and IAT score?"

RQ2: Ho/Null hypothesis: There is no significant difference of means of IAT score and sex.

Ha/Alternate hypothesis: There is a significant difference of mean of IAT score and sex.

RQ3: "Is there a mean difference among research site and IAT score?"

RQ3: Ho/Null hypothesis: There is no significant difference of means of IAT score and research site.

Ha/Alternate hypothesis: There is a significant difference of mean of IAT score and research site.

RQ4: "Is there a mean difference among race and IAT score?"

RQ4: Ho/Null hypothesis: There is no significant difference of means of IAT score and race.

Ha/Alternate hypothesis: There is a significant difference of mean IAT score and race.

RQ5: "Is there a mean difference among classification and IAT score?"

RQ5: Ho/Null hypothesis: There is no significant difference of means of IAT score and student classification.

Ha/Alternate hypothesis: There is a significant difference of mean of IAT score and student classification.

As discussed previously, this study used four phases of data analysis: A descriptive analysis provided an overview of the study respondents, Pearson's *r* analysis was used for research question one to analyze the relationship of IAT score and grade point average, and a linear regression (OLS) analysis was utilized to show if the independent variable (IAT score) is predictive of the dependent variable (grade point average). Next, analysis of variance (ANOVA) was used for research questions two through five to determine if there was a difference of means among the demographic variables of sex, research site, race and student classification. The next section presents the findings from the study, starting with the descriptive analysis as an overview of the study respondents.

Data Analysis and Findings

At the conclusion of the study in July 2019, 783 individuals responded to the instrument. After eliminating respondents who did not fulfill the research criteria for this study, as outlined in Chapter Three, the sample size for the study was 692, which was 88.4% (*n*=692) of respondents. The following sections present the descriptive statistics of the study and the statistical analysis addressing each research question.

Description of Study Respondents

Descriptive analysis provided detailed information for each of the variables of the study including sex, research site, race, student classification, grade point average, and Internet Addiction Test (IAT) score. Table 4.1 provides a visual representation of participant's self-reported sex, race, and classification.

Most respondents in this study, 63.9% (*n* =442) were female, with males comprising 35.4% (*n* =245), and 0.7% (*n* =5) individuals choosing not to answer. These statistics mirror current statistics that females make up a majority of traditionally-aged college students at postsecondary institutions in Oklahoma (U.S. Department of Education. Institute of Education Sciences, National Center for Education Statistics, 2019) (Table 4.1).

Table 4.1: Descriptive Data of Study: Sex, Race, and Classification

Demographic Variables	n	Study Percentage	OK Percentage
Sex			
Female	442	63.9	55.0
Male	245	35.4	44.0
Choose No Answer	5	00.7	
Total	692		
Race			
No Answer	11	1.6	
American Indian	16	2.3	8.0
Black/African American	72	10.4	9.0
Hispanic	73	10.5	8.0
Asian	30	4.3	3.0
Two or More	5	00.7	
White/Caucasian	485	70.1	55.0
Total	692		
Classification			
1st Year	184	26.6	
2nd Year	172	24.8	
3rd Year	148	21.4	
4th or More Years	187	27.0	
Total	692		

Furthermore, 70.1% (n = 485) of the students identified as white/Caucasian, 10.5% (n =73) identified as Hispanic, 10.4% (n =72) identified as Black/African American, 4.3% (n =30) identified as Asian and 2.3% (n =16) as American Indian. Finally, 1.6% (n =11) chose not to answer and 0.7% (n =5) chose two or more races. Table 4.1 presents the sex, race, and classification statistics for this study and the state of Oklahoma using the 2017 U.S. Department of Education IPEDS data. Furthermore, the respondents were spread across four classifications relatively balanced. Students who identified as 4th year or more were 27.0% (*n* =187), 26.6% (*n* =184) identified as 1st year students, 24.8% (*n* =172) marked second year students, and 21.4% (*n* = 148) selected third year student.

The study was conducted at three research sites. Table 4.2 depicts the descriptive data based on research site.

Table 4.2: Descriptive Data of Study: Research Site

Demographic Variables	n	Percentage
Research Site: Institution		
Institution #1 (Regional Public)	412	59.5
Institution #2 (Regional Private)	162	23.4
Institution #3 (Regional Private)	116	16.8
Abstained	2	00.3
Total	692	
Research Site: Institution Type		
Public Institution	412	59.5
Private Institution	278	40.2
Abstained	2	00.3
Total	692	

Students participating at the regional, public institution, (institution #1) comprised 59.5% (*n* =412). Students participating from institution #2 made up 23.4% (*n* =162), and 16.8% of the participants (*n* =116) were from the other regional, private institution (institution #3). The breakdown of public to private students participating in the study was 59.5% (*n* =412) public institution to 40.2% (*n* =278) private institution. Two students (.3%) abstained from selecting an institution.

Statistical Analysis

As previously outlined, the statistical analyses used to answer the research questions in this study were Pearson correlation (*r*), and linear regression (OLS) for research question one, and an analysis of variance (ANOVA) for research questions two through five. Assumptions for each analysis are presented with the accompanying research question and subsequent data analysis. This section presents each research question, accompanying assumptions, and the statistical results. Discussion and implications of the results of this study are found in Chapter Five.

Research Question #1: *"Is there a relationship between a student's Internet Addiction Test (IAT) score and grade point average?"* A Pearson *r* was used to address whether there was a relationship between IAT score and grade point average. The analysis found there was a significant, negative correlation between the two variables (r = -.320, n = 692, p = .000) for the two-tailed test (Table 4.3).

Table 4.3: Pearson correlation

		GPA	IAT Score
GPA	Pearson correlation	1.00	-.320**
	Sig. (2-tailed)		.000
	N	692	692
IAT Score	Pearson correlation	-.320**	1.00
	Sig. (2-tailed)	.000	
	N	692	692

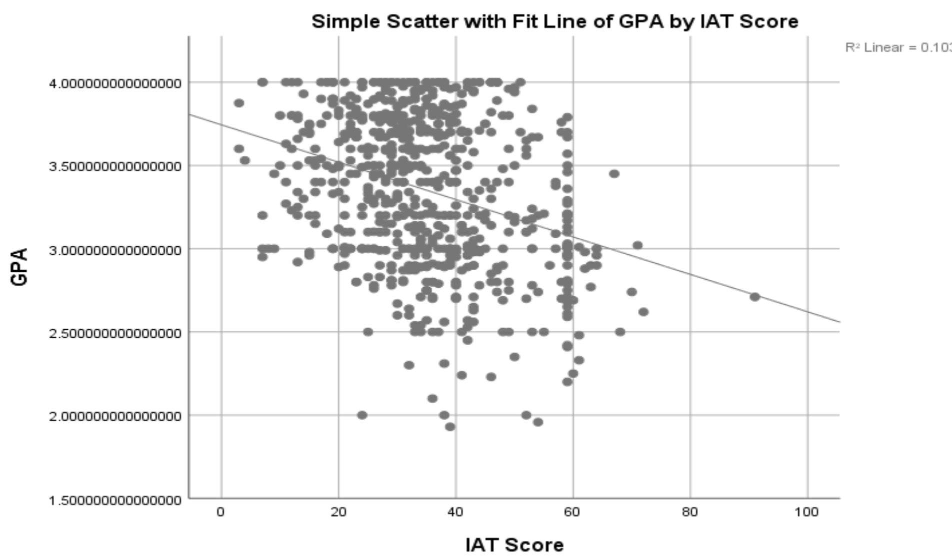
*** Correlation is significant at the .01 level (2-tailed)*

Considering the results for research question number one, finding a significant, negative correlation between IAT score and grade point average (r = -.320, n = 692, p = .000) (Table 4.3), the null hypothesis, *"There is not a significant correlation between IAT score and grade point average"* was rejected, and the directional hypothesis was retained, *"Student's scores on the IAT are significantly correlated with grade point average."*

After finding a relationship was present between IAT score and grade point average, a linear regression analysis was chosen to address if a student's IAT score predicted grade point average. Before conducting the regression, assumptions were analyzed.

As outlined in Chapter Three, simple linear regression (OLS) has four assumptions (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012). The first assumption is that there is a linear relationship between the dependent and independent variables. A scatter plot is used to test the linear nature of the variables and is presented in figure 4.1.

Figure 4.1: Scatter Plot of GPA and IAT score



The scatter plot shows a negative, linear association between a student's grade point average and IAT score.

After finding a linear association between grade point average and IAT score, the second assumption of normality of residuals was tested. For the test of normality of the residuals, a histogram and a probability plot were used (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012) (Figures 4.2 and 4.3).

Figure 4.2: Residual Probability Plot

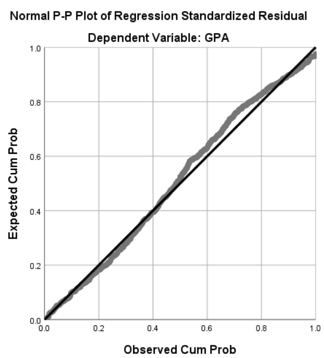
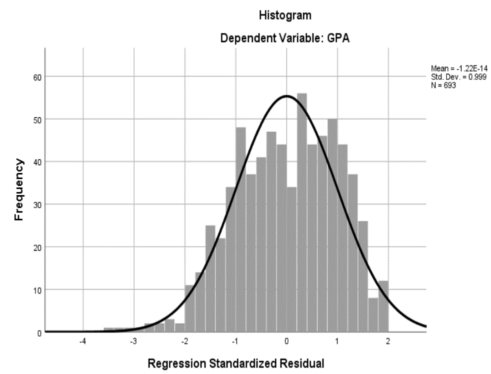


Figure 4.3: Histogram of Residuals



Both the probability plot and the histogram present a normal distribution of residuals, thus meeting the second assumption.

The third assumption for OLS is that autocorrelation is not present or is very minimal (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012). If the residuals are not independent from each other autocorrelation may occur. To test for autocorrelation, a scatterplot was used along with the Durbin-Watson test. The Durbin-Watson test analyzes the HO to see if the residuals are linearly correlated (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012).

The scatter plot in figure 4.4 shows the residuals falling more or less between 2 and -2 on the y axis and 3 and -3 along the x axis, thus autocorrelation appears not to be present. However, the Durbin-Watson test produced a test statistic of .154, (Table 4.4), indicating a likelihood of a positive autocorrelation of residuals, thus violating the assumption for autocorrelation. It should be noted that a limitation of the Durbin-Watson test is that it is to be interpreted in observations that have some sort of order present, like time sensitive studies (Field, 2013). That was not the case for this study, however, this failed assumption is a limitation of this study and is discussed previously in Chapter Three.

Figure 4.4: Scatterplot of residuals

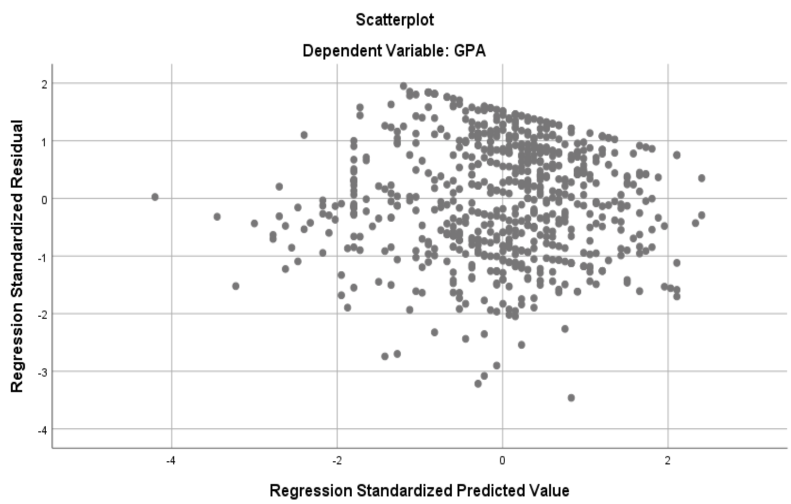


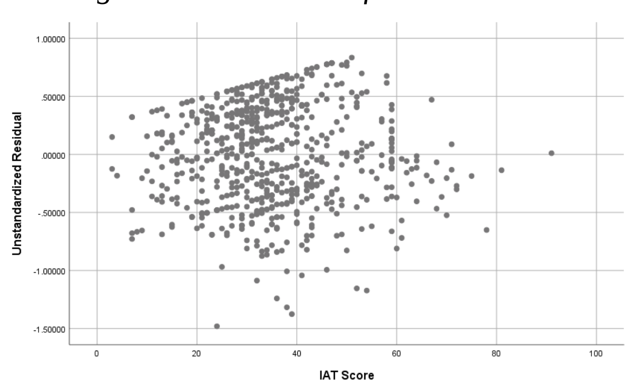
Table 4.4: Durbin-Watson test

Model	R	R Square	Adjusted R Square	Std. error of the estimate	Durbin-Watson
1	.341[a]	.116	.115	.4277113829	.154

a. Predictors: (Constant), IAT Score
b. Dependent Variable: GPA

A final assumption of OLS is constant variance of residuals. The variance assumption looks for residuals to exhibit constant variance with a mean equal or near zero. A scatterplot was used to test for variance in this study (Lomax & Hahs-Vaughn, 2012; Nolan & Heinzen, 2012) (Figure 4.5). The scatterplot shows the residuals are

Figure 4.5: Variance of Residuals



balanced along the mean of zero falling primarily between 1 and -1, thus the assumption is met.

Three of the four assumptions for linear regression were met with one, autocorrelation, not met. As previously mentioned, the autocorrelation violation is serious as it may create a greater significance when there is less significance or even no signification present. Again, this violation is a limitation of the study and is discussed in Chapter Three. Recognizing this, the results of the linear regression for this study should be interpreted with caution and are presented as such.

The simple linear regression was calculated to predict a student's grade point average based on the Internet Addiction Test (IAT) score. A significant regression equation was found ($F(1,690) = 78.958$, $p<.001$), with an R^2 of .103. The study participants' predicted grade point averages decreased 0.011 for every unit increase in IAT score. For this study, IAT score appears to predict at least ten percent of grade point average ($R^2 = .103$, $F(1,690)=78.958$, $p<.001$) (reference tables 4.5, 4.6 and 4.7).

Table 4.5: Linear Regression Model Summary

Model	R	R²	Adjusted R²	RMSE
1	0.320	0.103	0.101	0.431

Table 4.6: ANOVA

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	14.691	1	14.691	78.958	< .001
	Residual	128.380	690	0.186		
	Total	143.071	691			

Table 4.7: Coefficients

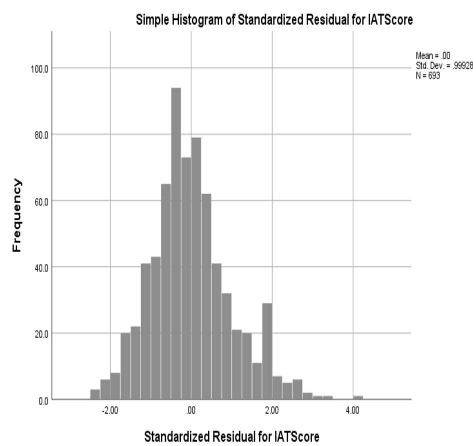
Model		Unstandardized	Standard Error	Standardized	t	p	95% CI Lower	95% CI Upper
1	(Intercept)	3.744	0.047		79.436	< .001	3.652	3.837
	IATScore	-0.011	0.001	-0.320	-8.886	< .001	-0.014	-0.009

Considering the results from the data analysis an influence may be found between IAT score and grade point average ($R^2 = .103$, $F(1,690)=78.958$, $p<.001$) (Tables 4.5, 4.6). For this study, a student's score on the IAT appears to predict grade point average, but the issue of autocorrelation assumption not being met should be noted.

For research questions two through five, a one-way ANOVA was chosen to statistically analyze the difference of means between descriptive variables and IAT scores. Refer to Appendix F for a complete overview of the ANOVA assumptions.

Research Question #2: "*Is there a mean difference among sex and IAT score.*" A one-way ANOVA was chosen to analyze if there was a mean difference among sex and IAT score. Sex was broken into two groups, female and male. A third category, "choose not to answer", had only five respondents and was omitted from the analysis because a robust analysis could not be conducted. Scores on the IAT were higher for men (*M*= 35.65, *SD*= 14.411) than for women (*M*= 34.61, *SD*= 12.634) (Table 4.8). Figure 4.6

Figure 4.6: Normal Distribution



presents a normally distributed histogram thus the assumption of normality was assumed. A Levene's test indicated an unequal variance between groups, (*F*= 3.008, *p*= .050*)* (Table 4.9), thus a Welch's ANOVA was conducted (Lomax & Hahs-Vaughn, 2012). The Welch's ANOVA between sex and IAT score did not yield a statistically significant difference between sex and IAT score (*F*(1, 10.668)= .715, *p*= .511) (Table 4.10).

Table 4.8: Descriptives: Sex and IAT Score

Sex	n	Mean	Std. Dev.	Std. Error	95% Confidence			
						Lower	*Upper*	*Min.*
Max.								
Female	442	34.61	12.634	.601	33.43	35.79	3	78
Male	245	35.65	14.411	.921	33.84	37.47	4	91
Total	687	35.02	13.316	.506	34.03	36.02	3	9

Table 4.9: Test of Homogeneity of Variances: Sex and IAT Score

		Levene Stat.	df1	df2	Sig.
IAT Score	Based on Mean	3.008	1	687	.050
	Based on Median	2.655	1	687	.071

Table 4.10: Robust Tests of Equality of Means: Sex and IAT Score

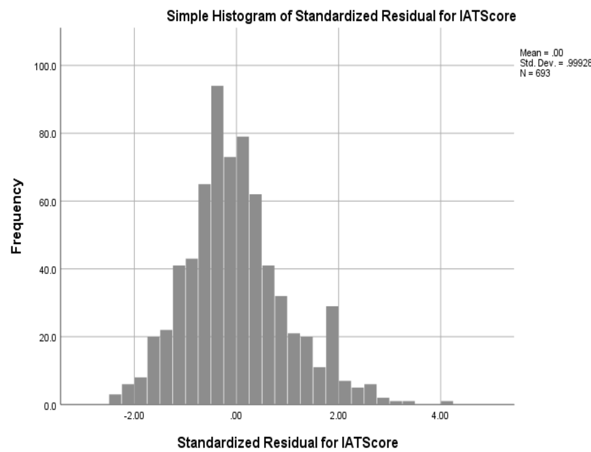
	Statistic[a]	df1	df2	Sig.
Welch	.715	1	10.668	.511

a. Asymptotically F distributed.

Considering the results from the data analysis for research question number two, there was not a difference in means between sex and IAT score (*F*(1, 10.668) = .715, *p* = .511) (Table 4.10). Because of this, the null hypothesis, *"There is not a significant* *difference of means of IAT score and sex"* was retained. The directional hypothesis, *"There is a significant difference of means of IAT score and sex",* was rejected. For this study, there was not a difference in means for a student's score on the IAT and sex.

Research Question #3: *Is there a mean difference among research site and IAT score?* A one-way ANOVA was chosen to analyze if there was a mean difference among research site and IAT score. Research was broken into two groups, public institution and private institution. The assumption of normality was assumed using a histogram showing a normal distribution of residuals (Figure 4.6).

Figure 4.6: Normal Distribution



Scores on the IAT were lower for students attending a public institution (*M*= 34.19, *SD*= 12.539) than for students attending a private institution (*M*= 36.38, *SD*= 14.286) (Table 4.11). A Levene's test indicated an unequal variance between groups, (*F*= 4.212, *p*= .041) (Table 4.12), thus a Welch's ANOVA was conducted (Lomax & Hahs-Vaughn, 2012). The Welch's ANOVA between research site and IAT score yielded a statistically significant difference between research site and IAT score (*F*(1, 541.243) = 4.330, *p* = .038) (Table 4.13).

Table 4.11: Descriptives: Research Site and IAT Score

Site	n	Mean	Std. Dev.	Std. Error	95% Confidence *Lower*	*Upper*	*Min.*	*Max.*
Public	412	34.19	12.539	.618	32.97	35.40	7	78
Private	278	36.38	14.286	.857	34.70	38.07	3	91
Total	690	35.07	13.304	.506	34.08	36.07	3	91

Table 4.12: Test of Homogeneity of Variances: Research Site and IAT Score

		Levene Stat.	df1	df2	Sig.
IAT Score	Based on Mean	4.212	1	688	.041
	Based on Median	3.523	1	688	.061

Table 4.13: Robust Tests of Equality of Means: Research Site and IAT Score

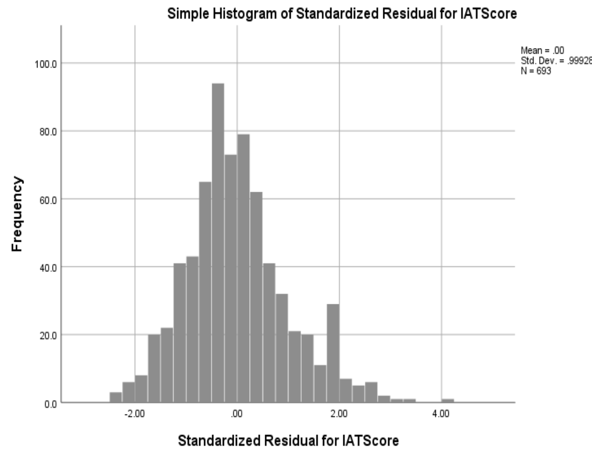
	Statistic[a]	df1	df2	Sig.
Welch	4.330	1	541.243	.038

a. Asymptotically F distributed.

Considering the results from the data analysis for research question number three, there was a significant difference in means between research site and student's scores and the IAT (F(1, 541.243) = 4.330, p = .038) (Table 4.13). Because of this, the null hypothesis, *"There is not a significant difference of means of IAT score and research site"* was rejected, and the directional hypothesis was retained, *"There is a significant difference of mean of IAT score and research site."* For this study, there was a difference in means for a student's score on the IAT and whether they attended a public institution or a private institution.

Research Question #4: *Is there a mean difference among race and IAT score?* A one-way ANOVA was chosen to analyze if there was a mean difference among a student's race and IAT score.

Figure 4.6: Normal Distribution



Race was broken into two groups, Caucasian and non-Caucasian. The assumption of normality is assumed using a histogram showing a normal distribution (Figure 4.6).

Scores on the IAT were lower for Caucasian students (*M*= 34.89, *SD*= 12.956) than for non-Caucasian students (*M*= 35.40, *SD*= 14.144) (Table 4.14). A Levene's test indicated an equal variance between groups, (*F*= 1.433, *p*= .232) (Table 4.15), thus an ANOVA was conducted (Lomax & Hahs-Vaughn, 2012). The ANOVA between race and IAT score did not yield a significant variation between race and IAT score at the p<.05 level ($F(1, 691) = .219$, $p = .640$) (Table 4.16).

Table 4.14: Descriptives: Race and IAT Score

Site	n	Mean	Std. Dev.	Std. Error	95% Confidence			
					Lower	*Upper*	*Min.*	*Max.*
Caucasian	485	34.89	12.956	.588	33.73	36.04	3	81
Non Cauc.	208	35.40	14.144	.981	33.47	37.34	3	91
Total	693	35.04	13.315	.506	34.05	36.03	3	91

Table 4.15: Test of Homogeneity of Variances: Race and IAT Score

		Levene Stat.	df1	df2	Sig.
IAT Score	Based on Mean	1.433	1	691	.232
	Based on Median	1.063	1	691	.303

Table 4.16: ANOVA: Race and IAT Score

	Sum of Squares	df	Square	F	Sig.
Between Groups	38.947	1	38.937	.219	.640
Within Groups	122650.840	691	177.498		
Total	122689.786	692			

Considering the results from the data analysis for research question number four, there was not a significant difference in means between race and student's scores and the IAT ($F(1, 691) = .219$, $p = .640$) (Table 4.16). Because of this, the null hypothesis, *"There is not a significant difference of means of IAT score and race"* was retained, and the directional hypothesis was rejected, *"There is a significant difference of means of IAT score and race."* For this study, there was not a difference in the means of a student's score on the IAT and race.

Research Question #5: *Is there a mean difference among classification and IAT score?* A one-way ANOVA was chosen to analyze if there was a mean difference among classification and IAT score. Classification was broken into two groups, first and second year students were underclass, whereas third, fourth and more students were upperclass. Figure 4.6 shows a normally distributed histogram, thus the assumption of normality is assumed. Scores on the IAT were higher for first and second year students (*M*= 36.67, *SD*= 14.057) than for third and fourth or more year students (*M*= 33.24*, SD*= 12.208) (Table 4.17). A Levene's test indicated an unequal variance between groups, (*F*= 8.254*, p*= .004*)* (Table 4.18), thus a Welch's ANOVA was conducted (Lomax & Hahs-Vaughn, 2012). The Welch's ANOVA between student classification and IAT score yielded a statistically significant difference between classification and IAT score ($F(1, 685.308) = 11.802$, $p = .001$) (Table 4.19).

Figure 4.6: Normal Distribution

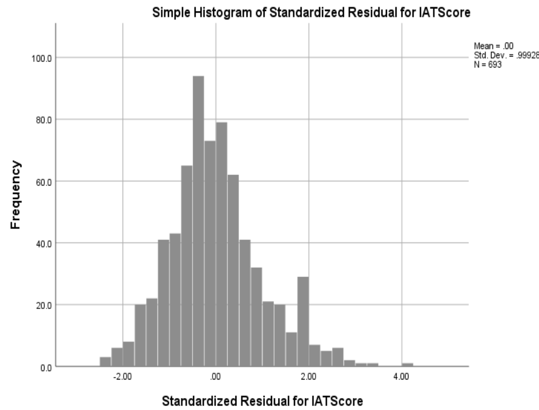


Table 4.17: Descriptives: Classification and IAT Score

Class	n	Mean	Std. Dev.	Std. Error	95% Confidence *Lower*	*Upper*	*Min.*	*Max.*
Under	356	36.67	14.057	.745	35.21	38.14	3	91
Upper	336	33.24	12.208	.666	31.93	34.55	3	81
Total	692	35.01	13.294	.505	34.02	36.00	3	91

Table 4.18: Test of Homogeneity of Variances: Classification and IAT Score

		Levene Stat.	df1	df2	Sig.
IAT Score	Based on Mean	8.254	1	690	.004
	Based on Median	5.860	1	690	.016

Table 4.19: Robust Tests of Equality of Means: Classification and IAT Score

	Statistic[a]	df1	df2	Sig.
Welch	11.802	1	685.308	.001

a. Asymptotically F distributed.

Considering the results from the data analysis for research question number five, there was a significant difference in means between student classification and the IAT ($F(1, 685.308) = 11.802$, $p = .001$) (Table 4.19). Because of this, the null hypothesis, *"There is not a significant difference of means of IAT score and student classification"* was rejected, and the directional hypothesis was retained, *"There is a significant difference of means of IAT score and student classification."* For this study, there was a difference in means for a student's score on the IAT and whether they were an underclass student or an upperclass student.

Summary

Chapter Four offered the findings of this study analyzing relationships among the Internet Addiction Test (IAT) and student-related factors. The findings showed a significant negative correlation between IAT score and grade point average and that a student's IAT score may predict their grade point average for study participants. Results of data analysis showed a difference of mean IAT scores for student classification and research site but not for race or sex. The following chapter discusses the findings for this study, presents the implications and recommendations, and considers future research.

CHAPTER V

DISCUSSION OF RESULTS

The increase in modern technological innovations across institutions of higher education affects college students in both positive and negative ways (Costley, 2014; Edwards, 2015; Fried, 2008; Mango, 2015). Although researchers have demonstrated technological enhancements lead to higher levels of student satisfaction and motivation for some students across higher education institutions in the United States (Costley, 2014; Kenney, 2011; Lin, & Yang, 2011), emerging research is beginning to show that similar technological innovations may have unintended, negative effects on students (Edwards, 2015; Fried, 2008). College students are presented with a plethora of distractions leading to less time studying than previous generations (Arum & Roska, 2011). Although distraction in the educational setting is not a new phenomenon, for modern college students, technology use leads the list of distractions, and college students are becoming addicted to technology at increasing rates (Agarwal & Kar, 2015; Young, 1998).

The purpose of this quantitative study was two-fold: analyze the relationship of the Internet Addiction Test (IAT) score and academic performance, and analyze any differences between student demographic variables and IAT scores. As discussed in Chapter Three, student success may be attributed to multiple confounding factors, many of which fall outside the scope of this study and serve as potential foci of future research. Confounding factors include but are not limited to: student mental health, a lack or inability to rise to the level of academic rigor in higher education, various forms of technology innovations vying for college students' time that may create distraction, and socio economic struggles hindering success in college. Despite these other possibilities, this study specifically focused on the increasing number of traditional college students struggling with varying levels of Internet addiction and if this struggle impacted student success.

While Chapter Four presented the statistical results from this study, Chapter Five focuses on a discussion of the results, and the significance and implications of these findings in higher education as it pertains to student success and technology addiction. This chapter contains five sections: summary of findings; discussion of findings; implications for theory, practice, and research; future research; and conclusions.

Summary of Study Findings

As presented in Chapter Four, this study found a negative relationship was present between students' IAT scores and grade point averages. As IAT scores increased, students' grade point averages decreased. Results showed that IAT scores may significantly predict grade point averages for this study's respondents, as demonstrated by ten percent of the variance in grade point average explained by the IAT score.

Additionally, the results of this study showed a difference in the mean IAT scores in relation to student classification and research site. First and second year students showed higher scores on the IAT as compared to third, fourth or more year students. When looking narrowly at study respondents who attended regional, private institutions, respondents scored higher on the IAT when compared to respondents who attended a public, research institution. Detailed results were provided in Chapter Four, Tables 4.4 – 4.18 and in Appendix G.

Technology use and subsequent Internet addiction in higher education are tricky topics because of digital natives' desire to use technology and enjoy its positive benefits (Barak & Dori, 2009; Tapscott, 2009; Thompson, 2013). As discussed previously, modern technology is prevalent across higher education and is producing numerous positive enhancements (Costly, 2014; Kenney, 2011; Mango, 2015). The issue arises when positive technological improvements result in some students experiencing technology addiction, one of the fastest growing addictions (Agarwal & Kar, 2015; Holden, 2001). It is critical to come to an understanding of potential technology addiction and the impacts on college student success.

Discussion of Findings

This study found a relationship between the Internet Addiction Test (IAT) score and college student success as measured by grade point average. Furthermore, there was a significant difference of means based on student classification and research site. The results of this study support a growing area of the literature (Krumrei-Mancuso, Newton, Kim, & Wilcox, D., 2013) suggesting that technology addiction is related to student success. Like this study shows, students with higher IAT scores may experience lower success in college. This section provides further discussion of the study's findings. These findings are discussed within the pertinent sections of the literature including the Internet Addiction and GPA, student classification, sex, and race.

Internet Addiction and GPA

The IAT was selected as a reliable instrument for this study based on a comparison of instruments utilized to assess technology addiction. For more in depth analysis on these instruments, refer to Chapter Two. For the study, the IAT showed varying levels of Internet use within the study participants ranging from lower levels of use to higher levels of Internet addiction. As was hypothesized, the higher the IAT score, indicating higher levels of Internet use and Internet addiction, the lower the student grade point average. Two theoretical frameworks, distraction-conflict theory and rational addiction theory were selected to inform the study findings. The following sections discuss the study findings using each of these theories.

Distraction-conflict. The finding that IAT scores have a negative relationship to grade point average also parallels with the distraction-conflict theoretical framework chosen for this study. Distraction-conflict theory posits that when a person is experiencing a challenging event or activity, like a college course or lecture, higher levels of distraction (or splitting of attention) lead to lower levels of learning or competence (Sanders, 1981). The literature on distraction-conflict theory indicates that students will struggle with complex tasks when higher levels of distraction are present (Nicholson, Parboteeah, Nicholson, & Valacich, 2005).

Because research in this area is very sparse, anecdotal information is currently what is available for considering how distraction-conflict *may* be at work in college classrooms and, therefore, of interest for future research. For example, enter any contemporary college classroom and you will see students with various types of technology – laptops, smartphones, etc., in addition to classroom technology. At any given time, it may be difficult for an instructor to know whether a student is using technology pertinent to the course or using technology for other pursuits. As the study findings show, students with higher IAT scores spend more time on technology, which suggests that an addicted student *may* be more likely, with phone or laptop in hand, to use the technology for more than just course-related activity. However, even if being used for course-related forays into cyberspace, this splitting of attention, and increased time on the Internet, would represent a distraction from the current academic work ongoing in the classroom. According to the theory and the results of the study, this may lead students to lower levels of success (or lower grade point averages). Given the lack of research in this area, clearly more research would be needed, however, this theory presents a provocative possibility for deepening our understanding of the possible implications.

Furthermore, distraction conflict theory suggests that the mere presence or thought of something that has previously caused distraction leads to lower levels of performance (Sanders, 1981). For example, just because a student may not have technology visible in the classroom, distraction may still be present because the student is still thinking about the most recent post on social media, or the buzzing phone in their pocket, wondering what they are missing. Was the student in the middle of an online game when class started and are still getting notifications from other players (i.e. the buzzing phone)? Was he or she in the middle of a text conversation and unwilling or unable to complete the conversation because of class starting? Distraction conflict submits continuing mental focus on this distraction would inhibit performance, or as this study shows, impact student success. Logic suggests that an Internet addicted student may struggle at greater levels but, again, additional research would need to be conducted.

Based upon use of the internet, the IAT helps identify students experiencing higher levels of Internet addiction, for whom just the presence of technology in a learning space, whether personal or classroom technology, may create a distraction for the student. With technology integrated into higher education learning practices and pedagogy and interwoven into much of the social space of college students, many students experiencing Internet addiction may struggle with academic success. The results of this study are aligned with this notion of distraction leading to lower levels of performance.

At the very least, technology is challenging students to make decisions related to time, technology use, and academic work. Students need to understand that spending more time using technology instead of academic pursuits likely will lead to lower levels of academic success. Whereas this may seem obvious, addicted students are willing to overlook the negative outcomes of choosing to spend time on the Internet rather than study or complete other academic work. The practical application of the IAT is discussed in the next section pertaining to Internet addiction analyzed with rational addiction theory, as well as later in this chapter.

Rational-addiction. Rational addiction theory further helps explain the finding that higher student IAT scores relate to lower grade point averages. As detailed in Chapter Two, rational addiction theory surmises that addicted individuals make conscious decisions to choose their addiction over better behavior. Concerning the topic of internet addicted students, rational addiction theory posits that students will choose technology use over healthy behaviors like studying (Becker & Murphy, 1988). For example, and related to this study, a student might choose to play a video game, or spend time on social media, at the expense of the grade on an assignment or course grade, thus, choosing the Internet and other forms of technology over academic success.

It is important to note, that rational addiction theory suggests that individuals are not blind to the future consequences of present actions and are actually *forward looking* (Becker & Murphy, 1988; Gruber & Koszegi, 2001). Thus, students who show higher levels of Internet addiction are not blind to the academic consequences of choosing time on technology over academic tasks, they rationally choose the addiction, even though they realize negative outcomes are possible. Consequently, pertaining to this study, this choice of addictive behavior leads to grade point averages that are lower. Like other addictions, students who are addicted to the Internet need support in college to help first, recognize the addiction and second, address the addictive desires, otherwise the addiction may lead to lower levels of success. Rational addiction theory stops short of providing intervention strategies, and this is discussed as a critique later in this chapter.

Student Classification

Student classification is a significant variable in retention and persistence research (Mayhew, et. al., 2016; Pascarella & Terenzini, 1998). Additionally, studies have researched Internet addiction related to a student’s classification (Young, 1998; Young, 2008). The findings in this study mirror previous research with younger students experiencing higher levels of Internet addiction (Young, 1998). In this study there was a significant difference in IAT test scores between first and second year respondents compared to third and fourth year or more respondents. In other words, traditionally aged students in their first two years of college scored higher on the IAT. The literature suggests that Internet and technology usage may decline throughout a traditional college students' time in college (Junco, 2015). For this study this appears to be the case because a major tenet of Internet addiction is time spent on technology.

As stated previously, it is critical that higher education leaders, scholars, and practitioners become aware of this emerging variable impacting student success. Recognizing, not only that Internet addiction is increasing, but also that first or second year students might be at higher risk of Internet addiction, higher education leaders and practitioners may begin to offer programming and other support services for traditionally aged first and second-year students. Recommendations for programming and practice are discussed later in this chapter.

Sex

Sex was chosen as a variable for this study because, like student classification, it is a commonly used variable not only in student success literature, but also in studies exploring Internet addiction. In this study there was not a significant difference between IAT scores and sex. Although this may not seem significant, it is important in its *difference* from most other studies. Most literature on technology use reports that male college students report higher levels of technology use and experience higher levels of Internet addiction (Kubey, Lavin & Barrows, 2001; Morahan-Martin & Schumacher, 2000; Young, 2008).

It was hypothesized that the male students in this study would score higher on the Internet Addiction Test. Although the male study respondents' mean scores were higher than the female IAT mean scores, there was not a significant difference in this study. Thus, the findings from this study showed that female IAT scores were not statistically different from male IAT scores. It is unknown whether the lack of significant difference between females and males IAT scores is an anomaly of this study, or if this study is providing an early indicator of increasing levels of Internet addiction for females. This divergence with the literature is further addressed in the future research section of this chapter regarding expanding the population of the study.

Race

Like sex, race is used widely as a variable in student success literature. Race is a significant indicator of student success with underrepresented students experiencing lower levels of success compared to the overrepresented students (Murtaugh, et. al, 1999; Peltier, et. al., 1999; Reason, 2001; Reason, 2009). Race was chosen for this study to explore if there was a difference between students' IAT scores from the majority culture (white) compared to students from minority cultures as a collective (non-white). The literature pertaining to race and the IAT is shallow with just a handful of Internet addiction studies exploring race as a demographic variable (Agarwal & Kar, 2015; Christakis, et. al., 2011; Hui-Jie, et. al., 2014). The researcher intended for this study to add to the body of literature in this area.

While there are strong ties between race and student success, for the study, there was not a significant difference in IAT scores between the two groups of students (white and non-white) based on race. This lack of significance could be rooted in many confounding factors, one of which is that underrepresented students tend have lower levels of access and subsequent use of technology in the home and in primary education (Jackson, et. al. 2008). This lack of access and technology use may limit the levels of

Internet addiction for underrepresented populations. Further study should be conducted regarding race and Internet addiction and is discussed later in the chapter.

Research Site

Unlike the other three variables, research site is not typically found in the literature on student success or Internet addiction. Research site was practically chosen as a variable for this study because the study participants were from both public and private higher education institutions. The study examined if there was a difference of mean IAT scores between private institution participants and public institution participants.

The results from this study found a significant difference of mean IAT scores with participants from private institutions scoring higher as compared to the participants from the public institution. This finding was surprising and may be rooted in different confounding variables. Participants from private institutions may be more affluent, thus have access to more forms of technology. Additionally, this affluence may provide the participants from private institutions more time because they might not need to work as many hours while in college. As the IAT assesses time spent on the Internet, private institution participants may have more time to spend on the Internet when compared to public institution participants, or this finding may be an anomaly; either way, this significance is intriguing. As with the other findings of this study, further research is recommended, continuing to explore if this finding is generalizable across traditional college students at both public and private institutions.

Implications

The following sections discuss the implications of the findings of this study as they relate to theory, practice, and research.

Theory

Theory provides a foundation and an informed view for every type of study, as well as a lens for better understanding the findings of a study (Anfara & Mertz, 2015). Two theoretical frameworks, rational addiction theory and distraction-conflict theory, informed this study and were previously discussed in this chapter, as well as in Chapters One and Two. Both theories were utilized during the design of the study and after the data analysis to further understand and interpret the results.

Rational Addiction Theory. Rational addiction theory helped shape the primary hypothesis for this study that students with higher IAT scores will have lower grade point averages. This hypothesis was selected primarily because the rational addiction theoretical framework noted that individuals struggling with addiction rationally choose the addiction over healthy behaviors. Thus, students who were addicted to the Internet would choose the Internet over healthy, academic behaviors.

Rational addiction theory helped explain the results of the study and provided a framework for why students choose to use technology, even if they know choosing technology will lead to lower levels of academic success. Furthermore, utilizing rational addiction theory assisted with recognizing the similarities of Internet addiction as compared with other addictions such as gambling or smoking. A critique of this theory, considering this study, is that rational addiction theory literature does not currently include technology addiction. With the literature on technology and Internet addiction still shallow, exploring the possible connections of this growing addiction to other, more recognizable and researched addictions is beneficial to help understand the potential impacts Internet addiction may have on students. Another critique is that rational addiction theory stops at identifying the addict's choice of addiction and does not provide practical guidance for support or intervention. Support and intervention for students struggling with Internet addiction is a critical step that needs to be addressed.

Understanding that technology addiction is rapidly increasing throughout society, it behooves educators to recognize and provide support for students wrestling with Internet addiction similar to ways support services are offered to students with other addictions. Rational addiction theory researchers should also continue to explore how rational addiction theory informs technology addiction and expand the scope of future studies to include this newer addiction.

Distraction Conflict Theory. Distraction conflict theory provided valuable understanding as to why students with higher IAT scores have lower grade point averages. This psychological theory informed the study results showing that higher levels of distraction lead to lower levels of performance. As mentioned previously, distraction conflict theory contends that the mere presence of the stimulus creating the addiction, in this case technology or even thinking about technology, may distract students (Nicholson, Parboteeah, Nicholson, & Valacich, 2005; Sanders, 1981). Furthermore, the difficulty with this topic of inquiry is that numerous forms of technology are present throughout higher education, not just in the classroom (Bellur, Nowak, & Hull, 2015; Cerretani, Iturrioz, & Garay, 2016; Junco, 2012; Zhang, 2015).

A critique of distraction conflict theory relating to this study is the difficulty trying to identify what distractions lead to lower levels of performance. Distractions are present throughout the academic setting and technology is just one of many. Distraction conflict theory applies a broad blanket to cover distractions, where this study attempted to take a more nuanced approach to identify specific technological addictions. Distractions created by technology use may be significant variable in the discussion or it may not. Future research should take a closer look specifically at technological distractions and student achievement, as this study sought to link the IAT to student success.

Helping students with higher levels of Internet addiction understand that distractions may inhibit performance is critical in supporting them along the academic journey. Giving Internet addiction credence alongside other addictions, while recognizing that Internet addicted students are interacting with the very item they are addicted to, often in academic settings, is a topic that educators and practitioners must address. The findings of this study, informed by both theoretical frameworks, provide higher education administrators, educators and practitioners with insights on how some students are wrestling with this growing addiction. Both rational addiction theory and distraction conflict theory align nicely in the arena of Internet addiction and student success and may be helpful in guiding future discussions, research, and practices.

Practice

The number of students entering higher education with technology addiction is increasing (Agarwal & Kar, 2015; Young 2008). Higher education practitioners and leaders would be well served to have an awareness of this phenomenon, begin to consider systems to identify technology addiction, and create systems to support students who may struggle with technology addiction. This section outlines three areas of implications of the study's findings related to higher education practice: identifying students with Internet addiction, supporting students with Internet addiction, and using technology wisely and intentionally in educational settings.

Identifying students with Internet addiction. Although the IAT was related to grade point average and appeared to be a predictor of GPA in this study, without additional knowledge from further study the researcher is hesitant to recommend using the IAT as a tool to help higher education leaders and practitioners identify students who struggle with Internet addiction. This is due to the extremely small influence IAT score had on GPA. As was presented in Chapter Four, the influence of IAT score on grade point average was .01. On a practical level, the impact on grade point average is negligible.

In this study, the total IAT score was used to test if the IAT predicted grade point average. Using the four IAT categories that make up the total score in future studies may provide a better understanding of which students are wrestling with problematic internet usage. As with most addictions, identification is critical to the process of providing support. As discussed throughout this study, students struggling with Internet addiction are likely to experience lower levels of student success. Early identification, perhaps with students entering higher education institutions, is key to providing support systems for students.

One example would be to for higher education practitioners to use a tool seeking to identify students struggling with Internet addiction in the new student orientation process, or shortly after first-year students begin college. Using the finding that first and second year students have higher IAT scores, helping students at the beginning of the academic experience realize personal Internet use may lead to lower levels of academic achievement is a critical step in setting the student up for success. Identifying students struggling with Internet addiction is the first step. Supporting students with Internet addiction is a second, critical component.

Supporting students with Internet addiction. College students are entering college with higher levels of depression, mental illness, and substance abuse such as alcohol or drug addictions as compared to previous generations (Hunt, 2010; Perron, et. al., 2011). As this study presents, technology addiction is a growing issue in addition to others listed. Because of the study's results, technology addiction should be added to the list of student issues that higher education leaders and practitioners need to be prepared to support and address. Student affairs professionals are routinely attempting to improve services for students struggling though addiction, and students report that these types of services offered by institutions greatly help academic success (Bell, et al., 2009).

Some examples of services offered to help students struggling with addiction and mental health issues are: coordinating and offering 12-step programs, offering counseling services from clinicians who are trained professionals, providing education opportunities for students struggling with addictions as well as for the broader campus community to help destigmatize addiction, and organizing events throughout the year promoting sober behavior and social networks on and off campus to help reduce peer pressure and relapse (Harris, Baker, & Cleveland, 20120; Perron, et. al., 2011). Furthermore, higher education practitioners should focus training on the addictions students are experiencing during a college experience.

As this study reports, technology addiction is a critical variable in student success and should be added to the list of traditional addictions like alcohol, sex, and drug addictions (Perron, et. al., 2011). Practitioners should create a system of referrals within the local community that are accepting of students suffering with addiction and mental health issues (Perron, et. al., 2011). Although new for many colleges and universities, services supporting technology addiction should be explored as well. Recognizing and identifying students with technology addiction and providing support services to help manage and overcome this addiction are vital to student success.

Using technology wisely in the formal academic setting. Educators should intentionally consider the pedagogical practice of implementing technology into courses, recognizing that some students struggle with Internet addiction. Literature stresses that done correctly, technology enhances learning in wonderful and meaningful ways (Bates & Poole, 2003; Harasim, 2011; Tondeur, et. al. 2017). However, considering this study's findings, if technology is introduced without the recognition that students may struggle with Internet addiction, technology may create an environment where students with higher levels of Internet addiction are more distracted, and therefore creating an environment where they may struggle academically.

It is recognized that distance learning requires high levels of technology innovation, but the use of technology in traditional classrooms can have successful outcomes as well, when implemented properly (Bates & Poole, 2003; Harasim, 2011). Bearing in mind the findings of this study, instructors should remain aware that some students might struggle with Internet addiction and recognize this as a potential issue when students are underperforming, offering support when practical. For onsite classes, instructors are encouraged to limit the personal use of technology when possible as this type of technology use may lead to distraction for some students (Bellur, Nowak, & Hull, 2015; Cerretani, Iturrioz, & Garay, 2016).

Scholars suggest that technology introduced in the classroom, whether traditionally or online, without clear intentions on the benefits to education and student learning outcomes, might have unintended consequences (Bates & Poole, 2003; Tondeur, et. al. 2017). Students struggling with Internet addiction may struggle with different forms of technological implementation. Furthermore, the use of technology in class may create distraction, or students using technology extensively may rationally choose distraction over academic pursuits. Understanding the way students interact with technological innovations is pertinent to the enhancement of education and the educational setting.

Research

As discussed previously, the literature and research on technology addiction and college student success is limited but growing steadily as additional studies are published. This study provides a starting point or base for future studies seeking to better understand how technology addiction is impacting college students and is also related to studies of student success, retention, and student engagement.

As previously posited, technology, more specifically, technology addiction, is a new variable that is emerging in higher education literature. Continued research is essential to help scholars and practitioners better understand precisely what implications technology has on college students. The following section presents possible recommendations for researchers along with future areas of research.

Future research

This study focused on the relationship of the Internet Addiction Test and the success of traditionally-aged college students in one region of the United States. While it expands the knowledge base, it is an early step in the understanding of Internet addiction and college student success. Using this study to grow the knowledge base on Internet addiction and college students, the researcher suggests future research in the following areas: student populations, types of technology, neurological impacts, different methodologies, and technology use and student engagement.

Student Populations

This study was bracketed to include only traditionally-aged (18-25) college students from public and private institutions in a specific geographic region. To increase generalizability, the researcher recommends broader studies both in geography and population, specifically expanding the population to older, non-traditionally-aged students.

Furthermore, this study found significance between a student's IAT score and classification as well as with the type of institution attended. Recognizing this, additional research specifically focusing on institution type and student classification might help deepen the understanding of the relationship between these specific groups' Internet addiction and student success. For example, younger students experience higher levels of Internet addiction (Young, 1998; Young, 2008). A future study focusing on entering first- year students' Internet addiction may help provide valuable insight to both scholars and practitioners.

Additionally, expanding the population of future studies might help better explain the disconnect of the literature pertaining to sex and Internet addiction. For this study it was predicted that sex would be a significant variable relating to IAT scores. Significance was not found for this study, but the literature on Internet addiction shows males to be more likely to become addicted to the Internet as compared to females. However, if not, or if this is a changing factor (e.g. female addiction is increasing to become on par with male), there are also important implications to be considered.

Types of Technology

A recommendation for future research centers on the types of technologies present for college student consumption, and how the different technologies lead to or do not lead to higher levels of technology addiction. It might be beneficial for future scholars to explore how students engage with different forms of technology. For instance, are gaming consoles as prevalent today as they were in the early 2000's (Kirriemuir, 2002) and, if so, how does this form of technology influence student success? With the rise of the smartphone over the past decade, has it taken the place of the laptop for student interaction, web searching, connection, or even research? This generation of college students seem to have more technology options available to them as compared to previous generations. The wide-array of options presents multiple areas for future research to help scholars and practitioners understand the ever growing and changing phenomenon of technology in higher education.

Neurological Impacts of Technology Addiction

This past decade researchers are starting to report that technology is changing how students learn (Gabriel, & Richtel, 2011; Ryan & Bagley, 2015). Scholars are attempting to better understand brain functioning with the influence of modern technology use. In Carr's (2010) book *The Shallows*, the author questions how the rise of the Internet and expedited access to information is changing the way we learn and, in some cases, potentially changing neuropathways. Carr (2010) cites numerous studies exploring the phenomenon of how a brain takes in information and processes it. In this same vein, scholars recommend further study on technology use and brain development (Gabriel, & Richtel, 2011; Liu et. al., 2015; Ryan & Bagley, 2015).

Literature is beginning to show that extended time exposed to technology produces changes to brain chemistry and development (Liu et. al., 2015). Future research that studies college students with high levels of Internet addiction in relation to learning, memory, and even neurological chemistry may help scholars better predict how students matriculate through the educational system. As was mentioned in the researcher's statement in Chapter One, very little oversight is given to new, technological advancement that we ingest at increasing rates. With this lack of oversight, scholars should step in, providing research that addresses this growing phenomenon.

Different methodologies

The use of different research approaches for future studies would expand knowledge both in practice and literature as it relates to college students and technology addiction. Although there are numerous opportunities to utilize different methods, the researcher recommends two methods for future studies: qualitative and longitudinal. Studies using varying approaches likely would provide different and valuable insights into the relationship between Internet addiction and student success.

Qualitative research method. Qualitative research is focused on depth and richness of the data rather than broad sweeping generalizations about a population (Creswell, 2014, Patton, 2015). Studying Internet addiction within the college student population using a qualitative method may provide a deeper, more nuanced understanding of students experiencing different levels of Internet addiction and technology use while working through the college experience. Qualitative studies might provide valuable insight into the individual student experience, helping shape a narrative of how modern technological innovation is changing the college student experience.

Individual interviews, researcher observations, and focus groups are just three of the approaches future researchers could implement to study college students and technology addiction through a qualitative lens. One possible qualitative study would be to interview a small group of students both in a focus group and individually in order to explore how students perceive personal and collective use of technology, and how that use is enhancing and detracting from educational experiences. The qualitative method is just one method that differs from this study. Another potential method is a longitudinal study.

Longitudinal method. Whereas this study captured data from one point in time, a longitudinal study would provide valuable insights and findings on how students interact with technology and may experience technology addiction over time. Longitudinal methods study a group of respondents over a time period, collecting data from these respondents at different points in time (Creswell, 2014; Patton, 2015). Longitudinal studies could follow a group of new students throughout their college experience, collecting data at a various points of the students' three to four to five year college journey. A study like this would provide understanding of a student's Internet addiction and technology usage and how it may change over time. A longitudinal study would contribute to the body of literature by exploring the struggles, across time, that college students may face with the distractions of modern technology innovations.

Like different pieces of a puzzle, different research methods would help create a fuller picture of the phenomenon being observed. Using different methods would enrich the work presented in this study and continue to build the body of literature in this, to date, relatively shallow area of study. The next section discusses future research suggested to help explore how college student engagement is impacted by modern technology.

Technology addiction and student engagement

Student engagement and experience has been a primary topic of research for decades in higher education (Pascarella & Terenzini, 1998; Tinto, 1987; Tinto, 1998), and currently, scholars are beginning to question how technology innovations are influencing college students (Mayhew, et. al., 2016; Turkle, 2012). This study and others like it raise questions about how students experiencing higher levels of Internet addiction are engaged on campus. College students, once walking and talking with each other across campus, now walk, oftentimes with earbuds in place, or staring at a screen, next to another student exhibiting similar behavior. How does this technology use influence student engagement? Considering technological innovations, how has engagement with peers and engagement with the life of the campus changed over the past decade?

Each of these areas of future research would provide valuable information to higher education leaders, scholars, and practitioners regarding modern technological innovation and the impacts on modern college students. It is critical that higher education leaders recognize that Internet addiction is a new variable, specifically considering this study and the increase of Internet addiction in college students. Furthermore, researchers should explore Internet addiction more broadly and deeply as it relates to wider populations and deeper student experiences. Modern technology is here to stay and continuing to research the intersection of technological innovation and college student experience and success is imperative over the upcoming decade.

Conclusion

This chapter summarized and discussed the study findings and provided the implications of this study for theory, practice, and research. Additional research is needed to better comprehend how Internet addiction is impacting college students, not only pertaining to grade point average, but socially through engagement, and cognitively relating to overall learning as well. This study provides an initial platform for future researchers to continue to explore intersections of technology use and distraction, Internet addiction, and student success in higher education.

As mentioned throughout this study, technology is woven into the fabric of contemporary higher education. The complexity of understanding the benefits of technological innovation, which are often quite visible, compounded with the potential detriments created by technology, which are often more difficult to recognize, makes this thread of inquiry quite challenging. Just as it would be unacceptable setting alcohol on the desk of an alcoholic in class, strangely enough, in some cases, this is what is happening to students with technology addiction. Students are asked to open a laptop and take notes, research, or work together on a shared google doc – interfacing with the very item of their addiction. For many reasons, including the many positive benefits technology brings to the higher education classroom, it is not realistic or useful to suggest that technology should not be present. However, coming to a better understanding, over the next decade, of how college students are engaging with technology, both positively and negatively, is critical.

This study explored the notion of Internet addiction and considered a tool (IAT) that practitioners and scholars could use to help identify struggling students. While the IAT did not demonstrate itself to be a "best tool" for higher education leaders, scholars, and practitioners, technology addiction is a newer phenomenon and growing in student populations, yet it is often difficult to identify. Likely more refined instruments to assess technology addiction will be developed. In the meantime, by recognizing Internet addiction as a potential new variable in the student success conversation, higher education leaders, scholars and practitioners will be able to provide more specialized support to students throughout the higher education experience in the hopes of increasing levels of student success.

REFERENCES

Adams, D. (2006). Wireless laptops in the classroom (and the Sesame Street syndrome). *Communications of the ACM, 49*(9).

Adams, S., Burns, M., & Southwest Educational Development Laboratory. Technology Assistance Program. (1999). *Connecting student learning & technology*. Austin, Tex: Technology Assistance Program, Southwest Educational Development Laboratory.

Agarwal, V., & Kar, S. K. (2015, July). Technology addiction in adolescents. *Journal of Indian Association for Child & Adolescent Mental Health*. pp. 170-174.

Aguilar-Roca, A., Williams, A., O'Dowd, D.K. (2012). The impact of laptop-free zones on student performance and attitudes in large lectures. *Computers & Education, 59*(4), 1300-1308.

American Psychiatric Association. (1994). *Diagnostic and statistical manual of mental disorders* (4th ed., text rev.). Washington, DC: Author.

Anderson, J.R. (2007). *How can the human mind occur in the physical universe?* New York, NY: Oxford University Press.

Anfara, V. A., & Mertz, N. T. (2015). Theoretical frameworks in qualitative research (2nd ed.). Los Angeles: Sage Publications.

Armstrong, L., Phillips, J. G., & Saling, L. L. (2000). Potential determinants of heavier Internet usage. *International Journal of Human - Computer Studies, 53*(4), 537-550. doi:10.1006/ijhc.2000.0400

Arum, R. & Roska, J. (2011). *Academically Adrift: Limited learning on college campuses.* Chicago, IL: University of Chicago Press.

Astin, A. W. (1964). Personal and environmental factors associated with college dropouts among high aptitude students. Journal of Educational Psychology, 55, 276–287.

Astin, A. W. (1975). Preventing students from dropping out. San Francisco: Jossey-Bass.

Astin, A. W., Korn, W., & Green, K. (1987). Retaining and satisfying students. Educational Record, 68, 36–42.

Astin, A. W. (1997). How ‘good’ is your institution’s retention rate? Research in Higher Education, 38, 647–658.

Baird, L. L. (1976). Using self-reports to predict student performance. College Entrance Examination Research Monograph, 7, 1-17.

Barak, M., & Dori, Y. J. (2009). Enhancing higher order thinking skills among in-service science education teachers via embedded assessment. Journal of Science Teacher Education, 20(5), 459–474

Barak, M., Lipson, A. Lerman, S. (2006). Wireless laptops as means for promoting active learning in large lecture halls. *Journal of Research on Technology in Education, 38*(3).

Bates, A.W., & Poole, G. (2003). *Effective Teaching with Technology in Higher Education.* Foundations for Success. San Francisco: Jossey-Bass.

Bauerlein, M. (2008). *The dumbest generation: How the digital age stupefies young Americans and jeopardizes our future*. New York: Penguin Group.

Bayer, A. E. (1968). The college dropout: Factors affecting senior college completion. Sociology of Education, 41, 305–316.

Becker, G. & Murphy, K. (1988). A Theory of Rational Addiction. *Journal of Political Economy, (96)*4, 675-699.

Bell, N. J., Kanitkar, K., Kerksiek, K. A., Watson, W., Das, A., Kostina-Ritchey, E., Harris, K. (2009). “It has made college possible for me”: Feedback on the impact of a university-based center for students in recovery. *Journal of American College Health, 57*, 650–657.

Bellur, S., Nowak, K.L., Hull, K.S. (2015). Make it our time: In class multitaskers have lower academic performance. *Computers in Human Behavior, 53,* 63-70.

Beranuy, M., Oberst, U., Carbonell, X., & Chamarro, A. (2009). Problematic Internet and mobile phone use and clinical symptoms in college students: The role of emotional intelligence. *Computers in Human Behavior, 25*(5), 1182-1187.

Biggs, J. B. (1987). Student approaches to learning and studying. Hawthorn: Australian Council for Educational Research.

Biggs, J. B., & Telfer, R. (1987). The process of learning (2nd ed.). Sydney: Prentice-Hall.

Bolliger, D. U., & Wasilik, O. (2009). Factors influencing faculty satisfaction with online teaching and learning in higher education. *Distance Education*, *30*(1), 103–116.

Braxton, J. M. (2000). Reworking the student departure puzzle. In J. M. Braxton (Ed.), Reworking the student departure puzzle (pp. 1–10). Nashville, TN: Vanderbilt University.

Bronfenbrenner, U. (2001). The bioecological theory of human development. In N. J. Smelser & P. B. Baltes (Eds.), International encyclopedia of the social and behavioral sciences (Vol. 10, pp. 6963–6970). New York: Elsevier.

Bowe, B. J., & Wohn, D. Y. (2015, July). Are there generational differences? Social media use and perceived shared reality. Proceedings of the social media and society conference. Toronto. New York, NY: ACM Press17.

Bowman, L., Levine, L., Waite, B.M., & Gendron, M. (2010). Can students really multitask? An experimental study of instant messaging while reading. *Computers & Education*, *54*(2010), 927-931.

Bridgeman B., McCamley-Jenkins L., & Ervin N., (2000). Predictions of freshman grade-point average from the revised and recentered SAT I: reasoning test (College Board Report No. 2000-1). New York: College Entrance Examination Board.

Caplan, S. E. (2002). Problematic Internet use and psychosocial well-being: Development of a theory-based cognitive-behavioral measurement instrument. Computers in Human Behavior, 18, 553-575.

Carr, N. (2010). *The shallows: What the Internet is doing to our brains.* W. W. Norton & Company: New York.

Cerretani, P.I., Iturrioz, E.B., Garay, P.B. (2016). Use of information and communications technology, academic performance and psychosocial distress in university students. *Computers in Human Behavior, 56*, 119-126.

Chang, M. K., & Law, S. P. M. (2008). Factor structure for young's Internet addiction test: A confirmatory study. *Computers in Human Behavior, 24*(6), 2597. doi:10.1016/j.chb.2008.03.001

Chen, Y.F., Peng, S.S. (2008). University students' Internet use and its relationships with academic performance, interpersonal relationships, psychosocial adjustment, and self-evaluation. *CyberPsychology & Behavior, 11*(4), 467-469.

Christen, A. (2009). Transforming the classroom for collaborative learning in the 21st century. *Techniques: Connecting Education and Careers*, 84 (1), 28-31.

Czaja, S. J., Charness, N., Fisk, A. D., Hertzog, C., Nair, S. N., Rogers, W. A., & Sharit, J. (2006). Factors predicting the use of technology: Findings from the center for research and education on aging and technology enhancement (create). *Psychology and Aging, 21*(2), 333-352.

Cole J.S, Gonyea R.M. (2010). Accuracy of self-reported SAT and ACT test scores: Implications for research. Res Higher Education. 51, 305–319.

Costley, K. C. (2014). The Positive Effects of Technology on Teaching and Student Learning. *Online Submission*.

Courage, M., Bakhtiar, A., Fitzpatrick, C., Kenny, S., Brandeau, K. (2015). Growing up multitasking: The costs and benefits for cognitive development. *Developmental Review (35)* March, 5-41.

Coyle, T., & Pillow, D. (2008). SAT and ACT predict college GPA after removing *g*. *Intelligence, 36*(6), 2008, 719-729.

Craik, K. J. W. (1948). Theory of the human operator in control systems: II. Man as an element in a control system. British Journal of Psychology, 38, 142–148.

Credé, M., & Kuncel, N.R. (2008). Study habits, skills, and attitudes: the third pillar supporting collegiate academic performance. *Perspectives on Psychological Science, 3*(6) 425-453.

Creswell, J. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). Los Angeles: SAGE Publications.

Dahlstrom, E. De Boor, T, Grunwald, P., Vockley, M. (2011). ECAR National Study of Undergraduate Students and Information Technology.

Davis, R. A. (2001). A cognitive-behavioral model of pathological Internet use. Computers in Human Behavior, 17, 187-195.

Davis, R., Fett, G., & Besser, A. (2002). Validation of a new scale for measuring problematic Internet use: Implications for pre-employment screening. CyberPsychology & Behavior, 5(4), 331-343.

Dede, C. (2004). Planning for “Neomillenia” learning styles: Implications for investments in technology and faculty. Cambridge, MA: Harvard Graduate School of Education

Delucchi, M., & Korgen, K. (2002). “We're the customer-we pay the tuition”: student consumerism among undergraduate sociology majors. *Teaching Sociology*, *30*, 100-107.

Derbyshire, K.L., Lust, K.A.. Schreiber, L., Odlaug, B.L., Christenson, G., Golden, D.J., Grant, J.E. (2013). Problematic Internet use and associated risks in a college sample. *Comprehensive Psychiatry, 54*(5), 415-422.

Dick, John (2013). Why Do Social Networks Increase Stress? The Anxiety of Facebook. *PsychCentral*. *Huffington Post*. Maldonado, Marissa (accessed November 2014).

Drouin M., Kaiser D. H., Miller D. A. (2012). Phantom vibrations among undergraduates: Prevalence and associated psychological characteristics. Computers in Human Behavior, 28, 1490-1496.

Eagan, K., Stolzenberg, E. B., Ramirez, J. J., Aragon, M. C., Suchard, M. R., & Hurtado, S. (2014). CIRP: The American freshman: National norms fall 2014. Los Angeles: Higher Education Research Institute, UCLA.

Edwards, P. H. (2015). Where Are We Going? *Quadrant Magazine*, *59*(4), 52.

Engstrom, C. M., & Kruger, K. W. (1997). *Using technology to promote student learning: Opportunities for today and tomorrow*. San Francisco: Jossey-Bass Publishers.

Engelberg, E., Sjoberg, L. (2004). Internet use, social skills, and adjustment. *CyberPsychology & Behavior*, *7*(1), 41-47.

Faraci, P., Craparo, G., Messina, R., & Severino, S. (2013). Internet addiction test (IAT): Which is the best factorial solution? *Journal of Medical Internet Research, 15*(10), e225.

Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics, 4th edition.* Thousand Oaks, CA: Sage Publications.

Frangos, C. C., Frangos, C. C., & Sotiropoulos, I. (2012). A meta-analysis of the reliability of Young's Internet Addiction Test. In Proceedings from the World Congress on Engineering. London, UK.

Fockert, J.D. (2013). Beyond perceptual load and dilution: a review of the role of working memory in selective attention. *Frontiers in Psychology, 4.*

Fried, J., & Verčič, A. (2011). Media preferences of digital natives' internal communication: A pilot study. *Public Relations Review, 37*(1), 84-86.

Frey M.C. & Detterman D.K. (2004). Scholastic assessment or *g*? The relationship Between the Scholastic Assessment Test and general cognitive ability. P*sychological Science, 15*, 73-378.

Fried, C.B. (2008). In-class laptop use and its effects on student learning *Computers & Education, 50(*3), 906-914.

Gabriel, T., & Richtel, M. (2011). A Classroom Software Boom, but Mixed Results Despite the Hype. September 14, *The New York Times.*

Gergen K. J. (2002). The challenge of absent presence. In Katz J. E., Aakhus M. (Eds.), Perpetual contact: Mobile communication, private talk, public performance (pp. 227-241). Cambridge, MA: Cambridge University Press.

Gergen K. J. (2003). Self and community in the new floating worlds. In Nyiri K. (Ed.), Mobile democracy: Essays on society, self, and politics (pp. 103-114). Vienna, Austria: Passagen Verlag.

Gerow, J.E., Galluch, P., Thatcher, J., (2010). To slack or not to slack: Internet usage in the classroom. *Journal of Information Technology Theory and Application (JITTA), 11* (3), 5-24.

Grace-Martin, M., Gay, G. (2001). Web browsing, mobile computing and academic performance. *Educational Technology & Society, 4*(3), 95-107.

Griffiths, M.D. (2000). Does Internet and computer ‘‘addiction’’ exist? Some case study evidence. *CyberPsychology & Behavior, 3*(1), 211–218.

Gruber J., & Koszegi, B. (2001). Is Addiction Rational? Theory and Evidence. *The Quarterly Journal of Economics*, 116(4), 1261-1303.

Guo, R., Dobson, T., & Petrina, S. (2008). Digital natives, digital immigrants: an analysis of age and ICT competency in teacher education. *Journal of Educational Computing Research, 38*(3), 235-254.

Haran, M. (2015). A History of Education Technology. Web Page Citation, May, 29, 2015.

Harris, K., Baker, A., & Cleveland, H. H. (2010). Collegiate recovery communities: What they are and how they are supported. In H. H. Cleveland, K. S. Harris, & R.P. Wiebe (Eds.), *Substance abuse recovery in College: Community Supported Abstinence.* New York, NY: Springer.

Hakoama, M., & Hakoyama, S. (2011). The impact of cell phone use on social networking and development among college students. *The American Association of Behavioral and Social Sciences Journal, 15*, 1-20.

Harasim, L. (2011). *Learning theory and online technology: How new technologies are transforming learning opportunities*. New York: Routledge Press.

Hargittai, E., & Hsieh, Y. (2010). Predictors and consequences of differentiated practices on social network sites. *Information, Communication & Society, 13*(4), 515-536.

Hill, J. (2011). Endangered childhoods: how consumerism is impacting child and youth identity. *Media, Culture & Society, 33,* 347-362.

Hembrooke, H. & Gay, G. (2003). The laptop and the lecture: the effects of multitasking in learning environments. *Journal of Computing in Higher Education*, *15*(1), 46-64.

Holden, C. (2001). 'Behavioral' addictions: Do they exist? *Science, 294*(5544), 980-982.

Hui-Jie, T., Hao-Rui, Z., & Wan-Seng, Y. (2014). The attraction of online games: An important factor for Internet Addiction. *Computers in Human Behavior, 30*(1), 321-327.

Humphreys L. (2005). Cellphones in public: Social interactions in a wireless era. New Media & Society, 7, 810-833.

Hunt, J., Eisenberg, D., & Kilbourne, A. M. (2010). Consequences of receipt of a psychiatric diagnosis for completion of college. *Psychiatric Services*, *61*, 399–404.

Immordino-Yang M. H., McColl A., Damasio H., Damasio A. (2009). Neural correlates of admiration and compassion. Proceedings of the National Academy of Sciences, 106, 8021-8026.

Ito, M., Baumer, S., Bittanti, M., Boyd, D., Cody, R., Herr-Stephenson, B. (2010). *Hanging out, messing around, and geeking out: Kids living and learning with new media: The John D. and Catherine T. MacArthur series on digital media and learning.* Cambridge, MA: MIT Press.

Jackson, L.A., Zhao, Y., Kolenic III, A., Fitzgerald, H.E., Harold, R. & Von Eye, A. (2008). Race, gender, and information technology use: the new digital divide. — Cyberpsychology and Behavior. 11: 437-442.

Junco, R. (2012). In-class multitasking and academic performance. *Computers in Human Behavior, 28* (6) 2236-2243.

Junco, R. & Cotten, R. (2012) No A 4 U: the relationship between multitasking and academic performance. *Computers & Education, 59,* 505-514.

Junco, R. (2015). Student class standing, Facebook use, and academic performance. *Journal of Applied Developmental Psychology, 36*(1), 18-29.

Just M. A., Keller T. A., Cynkar J. (2008). A decrease in brain activation associated with driving when listening to someone speak. *Brain Research, 1205*, 70-80.

Keller, G. (2001). The new demographics of higher education. *The Review of Higher Education*, 24, 219–236.

Kirriemuir, J. (2002). The relevance of video games and gaming consoles to the higher and further education learning experience. *Techwatch Report,* TSW 02.01. www.jisc.ac.uk/index.cfm?name=techwatch_report_0201, accessed 14 April.

Kuncel, N., Credé, M., Thomas, L. (2005). The Validity of Self-Reported Grade Point Averages, Class Ranks, and Test Scores: A Meta-Analysis and Review of the Literature. *Review of Educational Research*; *75*(1), 63-82.

Murdock, S. H., & Nazrul Hoque, M. (1999). Demographic factors affecting higher education in the United States in the twenty-first century. In G. H. Gaither (Ed.), Promising practices in recruitment, remediation, and retention. *New Directions for Higher Education, 108*, 5–14. San Francisco: Jossey-Bass.

Kennedy, G., Dalgarno, B., Bennett, S., Judd, T., Gray, K., & Chang, R. (2008). Immigrants and natives: investigating differences between staff and students' use of technology Hello! Where are you in the landscape of educational technology? *Proceedings Ascilite Melbourne 2008,* 484-492.

Kennedy, G., Judd, T., Churchward, A., Gray, K., & Krause, K. (2008). First year students' experiences with technology: are they really digital natives? *Australasian Journal of Educational Technology*, *24*(1), 108-122

Kenney, L. (2011). Elementary education, there's an app for that: communication technology in the elementary school classroom. *The Elon Journal of Undergraduate Research in Communications*, 2 (1), 67.

Kessler, S. (2011). 38% of college students can't go 10 minutes without tech. Mashable Tech. Retrieved from https://mashable.com/2011/05/31/college-tech-device-stats/#DrwKYJTk0Eqp.

Kim, H., et al. (2007). "Configurations of Relationships in Different Media." *Journal of Computer-Mediated Communication* 12(4): URL (consulted Oct. 2010): http://jcmc.indiana.edu/vol2012/issue2014/kim.html. Ling, R. S. (2008). New Tech, New Ties. Cambridge, MA, MIT Press.

Kolek, E.A., Saunders, D. (2008). Online disclosure: an empirical examination of undergraduate Facebook profiles. *NASPA Journal*, *45*(1), 1-25.

Krumrei-Mancuso, E. J., Newton, F. B., Kim, E., & Wilcox, D. (2013). Psychosocial Factors Predicting First-Year College Student Success. *Journal of College Student Development*, *54*(3), 247-266.

Kurt, S. (2010). Technology use in elementary education in Turkey: A case study. *New Horizons in Education*, 58 (1), 65-76.

Keyser, D., Wentworth, J., Middleton, H. (2014). Technology use and academic performance. *Computers & Education 78*(9), 306-311.

Kraushaar, J.M., & Novak, D.C. (2010). Examining the affects of student multitasking with laptops during the lecture. *Journal of Information Systems Education, 21*(2), 241-251.

Kubey, R.W., Lavin, M., Barrows, J.R. (2001). Internet use and collegiate academic performance decrements: Early findings. *Journal of Communication, 50*(2), 366-382.

Lauricella, S., & Kay, R. (2010). Assessing laptop use in higher education classrooms: the laptop effectiveness scale (LES). *Australasian Journal of Educational Technology, 26*(2), 151-163.

Lin Y.-H., Lin S.-H., Li P., Huang W.-L., Chen C.-Y. (2013). Prevalent hallucinations during medical internships: Phantom vibration and ringing syndromes. *PloS One, 8*(6), Article e65152.

Lin, W., & Yang, S. (2011). Exploring students' perceptions of integrating Wiki technology and peer feedback into English writing courses. *English Teaching: Practice and Critique*, *10*(2), 88-103.

Mardia, K.V. (1971). The Effect of Nonnormality on some multivariate tests and robustness to non-normality in the linear model. *Biometrika.* 58, 105-121.

Marois, R. & Ivanoff, J. (2005). Capacity limits of information processing in the brain. *Trends in Cognitive Science, 9*(6), 296-305.

McMurran, M. & Widyanto, L., (2004). The Psychometric Properties of the Internet Addiction Test. *CyberPsychology & Behavior*. *7*(4): 443-450.

Martin, A. J., Anderson, J., Bobis, J., Way, J., & Vellar, R. (2012). Switching on and switching off in mathematics: An ecological study of future intent and disengagement amongst middle school students. Journal of Educational Psychology, 104, 1–18.

Mayer, R.E., Moreno, R. (2003). Nine ways to reduce cognitive load in multimedia learning. *Educational Psychologist, 38*(1), 43-52.

Mayer, R.E. (2004). Should there be a three-strikes rule against pure discovery learning? The case for guided methods of instruction. *American Psychologist*, *59*(1), 14-19.

Mishra, P. & Koehler, M. (2009). Using the TPACK framework: you can have your hot tools and teach with them, too. *Learning & Leading with Technology (May)*, 14-18.

Mishra, P. & Koehler, M. (2006). Technological pedagogical content knowledge: a framework for teacher knowledge. *Teachers College Record, 108*(6), 1017-1054.

Misra S., Genevie J. (2013, May). The experience of place: How digital technologies are restructuring public places. Paper presented at the Environmental Design Research Association, Providence, RI.

Misra, S., Cheng, L., Genevie, J., & Yuan, M. (2016). The iPhone Effect: The Quality of In-Person Social Interactions in the Presence of Mobile Devices. *Environment and Behavior, 48*(2), 275.

Monsell, S. (2003). Task switching. *Trends in Cognitive Science, 7*(3), 134-140.

Morahan-Martin, J., & Schumacher, P. (2000). Incidence and correlates of pathological Internet use among college students. Computers in Human Behavior, 16, 13-29.

Muhterem, D., Yavuz, A. (2016). Effects of multitasking on retention and topic interest. *Learning and Instruction, 41*(Feb), 94-105.

Murtaugh, P. A., Burns, L. D., Schuster, J. (1999). Predicting the retention of university students. Research in Higher Education, 40, 355–371.

Nalwa, KP & Anand, A.P. (2003). Internet Addiction in Students: A Cause of Concern. *CyberPsychology & Behavior*. *6*(6): 653-656.

Navon, D., & Gopher, D. (1979). On the economy of the human-processing system. Psychological Review, 86, 214–255.

Nichols, L., A., & Nicki, R. (2004). Development of a psychometrically sound Internet addiction scale. Psychological Addiction Behavior, 18(4), 381-4.

Nicholson, D.B., Parboteeah, D.V., Nicholson, J.A., & Valacich, J.S. (2005). Using Distraction-Conflict Theory to Measure the Effects of Distractions on Individual Task Performance in a Wireless Mobile Environment. *Proceedings of the 38th Annual Hawaii International Conference on System Sciences*, 1-9.

Obermiller, C., Fleenor, P.. & Raven. P. (2005). Students as customers or products: perceptions and preferences of faculty and students. *Marketing Education Review*, *15* 27-36.

Patton, M. (2013). *Qualitative Research & Evaluation Methods* (3rd Edition). Thousand Oaks: CA, Sage Publications.

Peltier, G. L., Laden, R., Matranga, M. (1999). Student persistence in college: A review of research. Journal of College Student Retention, 1, 357–376.

Reason, R. D. (2001). The use of merit-index measures to predict between-year retention of undergraduate college students. Unpublished doctoral dissertation, Iowa State University.

Roby, T., Ashe, S., Singh, N., & Clark, C. (2013) "Shaping the Online Experience: How Administrators Can Influence Student and Instructor Perceptions through Policy and Practice." *The Internet and Higher Education 17*(C), 29-37.

Pennebaker, J. W., et al. (2001). *Disclosing and sharing emotion: Psychological, social, and health consequences*. Handbook of Bereavement Research: Consequences, Coping, and Care. American Psychological Association: 517-543.

Prensky, M. (2001). *Digital game-based learning.* McGraw-Hill: New York.

Przybylski A. K., & Weinstein N. (2013). Can you connect with me now? How the presence of mobile communication technology influences face-to-face conversation quality. Journal of Social and Personal Relationships, 30, 237-246.

Ohio State University. (2009). Facebook use linked to lower grades in college. *Science Daily, 4*.

Ophir, E., Nass, C., & Wagner, A.D. (2009). Cognitive control in media multitaskers: Proceedings of the National Academy of Sciences of the United States of America. *Social Sciences – Psychological and Cognitive Science, 106*(37), 15583-15587.

Pasek, J., More, E., Hargittai, E. (2009). Facebook and academic performance: reconciling a media sensation with data. *First Monday, 14*(5).

Perrin, A., & Duggan, M. (2015, June 26). American's Internet Access: 2000-2015. *Pew Research Center*. Retrieved from http://www.pewInternet.org/2015/06/26/americans-Internet-access-2000-2015/

Perron, B., Grahovac, I., Uppal, J., Granillo, T., Shutter, J., & Porter, C. (2011) Supporting Students in Recovery on College Campuses: Opportunities for Student Affairs Professionals. *Journal of Student Affairs Research and Practice, 48*(1), 47-64, DOI: 10.2202/1949-6605.6226

Prensky, M. (2001). Digital natives, digital immigrants, part 1. *On the Horizon, 9*(5), 1-12.

Prensky, M. (2008). Turning on the lights. *Educational Leadership, 65*(6) (2008), 40-45.

Ragan, E., Jennings, S., Massey, J., & Doolittle, P. (2014). Unregulated use of laptops over time in large lecture classes. *Computers & Education Volume 78*(9), 78-86.

Ravizza, S., Hambrick, D., & Fenn, K. (2014). Non-academic Internet use in the classroom is negatively related to classroom learning regardless of intellectual ability. *Computers & Education, 78*, 109-114.

Reason, R. D. (2001). The use of merit-index measures to predict between-year retention of undergraduate college students. Unpublished doctoral dissertation, Iowa State University.

Reason, R.D. (2009). Student Variables that Predict Retention: Recent Research and New Developments. *NASPA Journal, 46*(3), 482-501.

Richtel, M. (2012). Technology is changing how students learn, teachers say. *New York Times.*

Rideout, V.J., Foehr, U., & Roberts, D.F. (2010). *Generation M2: Media in the lives of 8- to 18-year-olds.* Kaiser Family Foundation.

Robbins, S., Lauver, K, Le, H., Davis, D., Langly, R., & Carlstrom, A. (2004). Do psychosocial and study skill factors predict college outcomes? A meta-analysis. *Bulletin*, *130*(2), 261-288.

Rosen, L.D. (2010). *Rewired: Understanding the iGeneration and the way they learn.* New York: Palgrave Macmillan.

Ryan, T. & Bagley, G. (2015). Nurturing the Integration ofTechnology in Education. *Journal of Theory and Practice in Education*, *11*(1), 33-50.

Sana, F., Weston, T., & Cepeda, N.J. (2013). Laptop multitasking hinders classroom learning for both users and nearby peers. *Computers & Education, 62*, 24-31.

Samson, P.J., (2010). Deliberate engagement of laptops in large lecture classes to improve attentiveness and engagement. *Computers in Education*, *1*(2), 1-19.

Sanders, G. S. (1981). Driven by distraction: An integrative review of social facilitation theory and research. *Journal of Experimental Social Psychology, 17*(3), 227-251.

Sanders, G.S., Baron, R.S., & Moore, D.L. (1978). Distraction and Social Comparison as Mediators of Social Facilitation Effects. *Journal of Experimental Social Psychology, 14*(3), 291-303.

Schwartz J., Beaver K. (2014). Making (up) the grade? Estimating the genetic and environmental influences of discrepancies between self-reported grades and official GPA scores. *Youth Adolescence,*44, 1125–1138.

Simkova, B., & Cincera, J. (2004). Internet addiction disorder and chatting in the Czech Republic. CyberPsychology & Behavior, 7(5), 536-539.

Small, G., & Vorgan, G. (2008). *Brain: Surviving the technological alteration of the modern mind.* Harper: New York.

Song, I., Larose, R., Eastin, M. S., & Lin, C. A. (2004). Internet gratifications and Internet addiction: On the uses and abuses of new media. CyberPsychology & Behavior, 7(4), 384-394.

Soule, L. C., Shell, L. W., & Kleen, B. A. (2003). Exploring internet addiction: Demographic characteristics and stereotypes of heavy internet users. The Journal of Computer Information Systems, 44(1), 64-73.

Srivastava L. (2005). Mobile phones and the evolution of social behaviour. Behaviour & Information Technology, 24, 111-129.

Sticca, F., Goetz, T., Bieg, M., Hall, N.C., Eberle, F., Haag, L., Einhäuser, W. (2017). Examining the accuracy of students' self-reported academic grades from a correlational and a discrepancy perspective: Evidence from a longitudinal study. *PLoS ONE*, 12(11), 1-13.

Stone A., Bachrach C., Jobe J., Kurtzman H., Cain V. (1999). The science of self-report: Implications for research and practice. *Psychology Press*, Mahwah, N.J.

Stone L. (2007). Living with continuous partial attention. Harvard Business Review, 85(2), 28-29.

Suhail, K., & Bargees, Z. (2006). Effects of excessive Internet use on undergraduate students in Pakistan. CyberPsychology & Behavior, 9(3), 297-309.

Sweller, J. (1994). Cognitive Load Theory, Learning Difficulty and Instructional Design. *Learning and Instruction, 4*, 295-312.

Sweller, J., Van Merrienboer, J., & Paas, F. (1998). Cognitive Architecture and Instructional Design. *Educational Psychology Review, 10*, 251-296.

Talento-Miller E, Peyton J. (2006). Moderators of the accuracy of self-report Grade Point Average. *Graduate Management Admission Council*; Report No.: 06–10.

Tapscott, D. (2009). *Grown up digital: How the net generation is changing your world.* McGraw-Hill: New York.

Taneja, A., Fiore, V., & Fischer, Briana, (2015). Cyber-slacking in the classroom: Potential for digital distraction in the new age. *Computers & Education, 82*(March), 141-151.

Tapscott, D. (2009). Grown up Digital: How the net generation is changing your world. NY: McGraw-Hill.

Telford, C. W. (1931). The refractory phase of voluntary and associative response. Journal of Experimental Psychology, 14, 1–35.

Thompson, P, (2013). The Digital Natives as Learners: Technology Use Patterns and Approaches to Learning. *Computers & Education, 65*, 12-33.

Tinto, V. (1987). Leaving college: Rethinking the causes and cures of student attrition. Chicago: University of Chicago Press.

Tinto, V. (1998). Colleges as communities: Taking research on student persistence seriously. The Review of Higher Education, 21, 167–177.

Turel, O. (2015). An Empirical Examination of the "Vicious Cycle" of Facebook Addiction. *Journal of Computer Information Systems*, *55*(3), 83-91.

Turkle S. (2012). Alone together: Why we expect more from technology and less from each other. New York, NY: Basic Books.

Turner, R. J., et al. (1995). "The Epidemiology of Social Stress." *American Sociological Review.* 60(1): p. 104-125.

Twenge, J. M., Martin, G. N., & Campbell, W. K. (2018). Decreases in Psychological Well-Being among American Adolescents after 2012 and Links to Screen Time during the Rise of Smartphone Technology. *Emotion.* Advance online publication.

Vaughan, R. P. (1968). College dropouts: Dismissed vs. withdrew. Personnel and Guidance Journal, 46, 985–689.

Velezmoro, R., Lacefield, K., & Roberti, J. W. (2010). Perceived stress, sensation seeking, and college students' abuse of the Internet. *Computers in Human Behavior*, *26*(6).

Wentworth, D., Middleton, J.H. (2014). Technology use and academic performance. Computers & Education 78, (September), 306-311.

Weaver, B., & Nilson, L. (2005). Laptops in class: what are they good for? What can you do with them? *New Directions for Teaching and Learning, 2005*(101), 3-13.

Wei, W. (2001). Internet dependency and psychosocial maturity among college students. *International Journal of Human-Computer Studies*, *55*(6), 919-938.

Welford, A. T. (1952). The "psychological refractory period" and the timing of high speed performance: A review and a theory. British Journal of Psychology, 43, 2–19.

Widyanto, L., Griffiths, M.D., Brunsden, V. (2011). A Psychometric Comparison of the Internet Addiction Test, the Internet-Related Problem Scale, and Self-Diagnosis. *Cyberpsychology, Behavior, and Social Networking*, 14(3), 141-149.

Wurst, C., Smarkola, C., & Gaffney, M. (2008). Ubiquitous laptop usage in higher education: effects on student achievement, student satisfaction, and constructivist measures in honors and traditional classrooms. *Computers & Education, 51*(4), 1766-1783.

Yang, D. J. (2000). Craving your next web fix: Internet addiction is no laughing matter. *U.S. News and World Report, 128*(2), 41.

Young, K. S. (1996). Psychology of computer use: XL. Addictive use of the Internet: A case that breaks the stereotype. Psychological Reports, 79, 899-902.

Young, K. S. (1998). Caught in the net: How to recognize the signs of Internet addiction and a winning strategy for recovery. New York: Wiley.

Zajonc, R.B. (1965). Social Facilitation. *Science, 149*, 269-274.

Zhang, W. (2015). Learning variables, in-class laptop multitasking and academic performance: A path analysis. *Computers & Education, 81*, 82-88.

APPENDICES

APPENDIX A

Internet Addiction Test (IAT) questions (Young, 1998).

INTRODUCTION

The Internet Addiction Test (IAT; Young, 1998) is a 20-item scale that measures the presence and severity of Internet dependency among adults. Dr. Kimberly Young, a professor at St. Bonaventure University and director of the Center for Internet Addiction Recovery, developed the IAT to assess symptoms of Internet Addiction and compulsivity in a variety of test settings.

Appropriate Uses

The IAT measures the severity of self-reported compulsive use of the Internet for adults and adolescents. Results from the IAT should be interpreted with caution among clinical populations that suffer from psychiatric conditions concurrent with compulsive syndromes. The scale was created by adapting DSM-IV criteria for pathological gambling and is a modification of the earlier 8 item scale, Young's Internet Addiction Diagnostic Questionnaire (IADQ). The IAT views Internet Addiction as an impulse-control disorder and the term Internet refers to all types of online activity. The IAT is the most widely used Internet Addiction scale and the test has been translated in several languages including English, Chinese, French, Italian, Turkish, and Korean.

User Qualifications

The IAT may be administered and scored by paraprofessionals, but it should be used and interpreted best by professionals with appropriate clinical training and experience according to the guidelines established by the American Psychological Association's *Standards for Educational and Psychological Tests* (1985). Clients with Internet Addiction frequently have co-morbid mood disorders, and some clients with mood disorders, in turn, may report suicidal ideation. Therefore, the clinician reviewing the IAT data must be able to respond to a client's addictive disorder as well as the client's depression or suicidal ideation.

ADMINSTRATION

Administration
The IAT presents few difficulties in administration. The testing environment in which the IAT is given must provide the client with sufficient illumination for reading and be quiet enough to afford concentration. Obviously, the test administrator must determine beforehand whether or not a client can comprehend the IAT's item content.

Administration Time
The IAT requires between 5 to 10 minutes to complete when it is self-administered. Oral administration generally takes 10 minutes.

Respondents are asked to answer with rarely, occasionally, frequently, often, always, does not apply.

1. How often do you find that you stay online longer than you intended?

2. How often do you neglect household chores to spend more time online?

3. How often do you prefer the excitement of the Internet to intimacy with your partner?

4. How often do you form new relationships with fellow online users?

5. How often do others in your life complain to you about the amount of time you spend on-line?

6. How often do your grades or schoolwork suffer because of the amount of time you spend on-line?

7. How often do you check your email before something else that you need to do?

8. How often does your job performance or productivity suffer because of the Internet?

9. How often do you become defensive or secretive when anyone asks you what you do online?

10. How often do you block out disturbing thoughts about your life with soothing thoughts of the Internet?

11. How often do you find yourself anticipating when you will go on-line again?

12. How often do you fear that life without the Internet would be boring, empty, and joyless?

13. How often do you snap, yell, or act annoyed if someone bothers you while you are online?

14. How often do you lose sleep due to late-night logins?

15. How often do you feel preoccupied with the Internet when off-line, or fantasize about being online?

16. How often do you find yourself saying “just a few more minutes” when on-line?

17. How often do you try to cut down the amount of time you spend on-line and fail?

18. How often do you try to hide how long you've been on-line?

19. How often do you choose to spend more time on-line over going out with others?

20. How often do you feel depressed, moody, or nervous when you are off-line, which goes away once you are back online?

SCORING

Guidelines
The IAT total score is the sum of the ratings given by the examinee for the 20 item responses. Each item is rated on a 5-point scale ranging from 0 to 5. The maximum score is 100 points.

The IAT total score ranges, with the higher the score representing the higher level of severity of Internet compulsivity and addiction. Total scores that range from 0 to 30 points are considered to reflect a normal level of Internet usage; scores of 31 to 49 indicate the presence of a mild level of Internet Addiction; 50 to 79 reflect the presence of a moderate level; and scores of 80 to 100 indicate a severe dependence upon the Internet. Research addressing the sensitivity and validity of these score ranges is published in several journals. The IAT is validated in several languages so the examiner should review the correct study based on the language used for administration.

The examiner should evaluate the score ranges for the purposes for which the IAT is being used. If the examiner’s purpose is to measure detection of persons with Internet Addiction, then the upper level of each range should be lowered to minimize false negatives. This method would be useful in screening for possible cases of Internet Addiction. To reduce the number of false positives, the examiner should raise the upper level of each range. This method is used in research for which one wishes to obtain as pure a sample as possible of persons with Internet Addiction.

Interpretation

Because a IAT total score yields only an estimate of the overall severity of Internet Addiction being described by a person, the examiner must consider other aspects of psychological functioning exhibited by the person, particularly any co-morbid symptoms of chronic impulsively, clinical depression, or relational difficulties that may elevate scores. A review of the more recent validation studies will help in looking at closer analyses of the test. The examiner should also inspect the IAT score for a pattern of symptom complaints as follows:

<u>Salience – questions 10, 12, 13, 15, and 19.</u>
High ratings for Salience-related exam items indicate that the respondent most likely feels preoccupied with the Internet, hides the behavior from others, and may display a loss of interest in other activities and/or relationships only to prefer more solitary time online. High ratings also suggest that the respondent uses the Internet as a form of mental escape from distributing thoughts and may feel that life without the Internet would be boring, empty, or joyless.

<u>Excessive Use – questions 1, 2, 14, 18, and 20</u>
High ratings for Excessive Use-related items indicate that the respondent engages in excessive online behavior and compulsive usage and is intermittently unable to control time online that he or she hides from others. High ratings also suggest that the respondent is most likely to become depressed, panicked, or angry if forced to go without the Internet for an extended length of time.

<u>Neglect Work – questions 6, 8, and 9</u>
High ratings for Neglect Work-related exam items indicate the respondent may view the Internet as a necessary appliance akin to the television, microwave, or telephone. Job or school performance and productivity are most likely compromised due to the amount of time spent online and the respondent may become defensive or secretive about the time spent online.
<u>Anticipation – questions 7, 11</u>
High ratings for Anticipation-related items indicate that the respondent most likely thinks about being online when not at the computer and feels compelled to use the Internet when offline.

<u>Lack of Control – questions 5, 16, and 17</u>
High ratings for Lack of Control-related items indicate that the respondent has trouble managing his or her online time, frequently stays online longer than intended, and others may complain about the amount of time he or she spends online.

<u>Neglect Social Life – questions 3 and 4.</u>
High ratings for Neglect of Social Life-items indicate the respondent most likely utilizes online relationships to cope with situational problems and/or to reduce mental tension and stress. High ratings also suggest that the respondent frequently forms new

relationships with fellow online users and uses the Internet to establish social connections that may be missing in his or her life.

APPENDIX B

Email Template and IRB Consent Form

To: Student Email Address

From: mhoustonphd1@gmail.com

Subject: Technology and Student Success

My name is Michael Houston, and I am a doctoral student at Oklahoma State University. For my doctoral program, I am studying how technology use impacts college students. I have created a short survey that I am sending college students throughout Oklahoma to help better understand technology usage. This survey takes just a few minutes to complete (about 5).

I ask that you **click on the link below** and answer the questions to the best of your ability. The results are completely confidential and anonymous. If you have any questions, please reply to this email. Thanks in advance for helping with my study, and I hope you have a great finish to this year!

https://okstatecoe.az1.qualtrics.com/jfe/form/SV_bNMn9uAVKh5ZkG1

Blessings,
Michael

College of Education, Health and Aviation

Adult Consent Form

THE EFFECTS OF INTERNET ADDICTION ON COLLEGE STUDENTS: A STUDY OF THE RELATIONSHIP BETWEEN THE INTERNET ADDICTION TEST AND COLLEGE STUDENT DEMOGRAPHICS AND ACADEMIC ACHIEVEMENT.

Background Information

You are invited to be in a research study of Technology Use and Student Success. We ask that you read this form and ask any questions you may have before agreeing to be in the study. Your participation in this research is voluntary. There is no penalty for refusal to participate, and you are free to withdraw your consent and participation in this project at any time. You can skip any questions that make you uncomfortable and can stop the interview/survey at any time. Your decision whether or not to participate in this study will not affect your grades.

This study is being conducted by: Michael Houston, School of Educational Foundations. Leadership and Aviation ,under the direction of Dr. Kerri Kearney, School of Educational Foundations , Leadership and Aviation.

Procedures

If you agree to be in this study, we would ask you to do the following things:

Click on the link to the survey. Answer the survey questions to the best of your ability by clicking on the appropriate response.

Participation in the study involves the following time commitment: 3-5 minutes.

Compensation

You will receive no payment for participating in this study.

PLEASE NOTE: This study contains a number of checks to make sure that participants are finishing the tasks honestly and completely. As long as you read the instructions and complete the tasks, your HIT will be approved. If you fail these checks, your HIT will be rejected.

Confidentiality

Only the Primary Investigator (PI), Doctoral Adviser and OSU IRB (if requested) have access to the data. All data is stored on the PI's hard drive which is stored on a password protected computer in a locked office. The information your give in the study will be anonymous. This means that your name will not be collected or linked to the data in any way. The researchers will not be able to remove your data from the dataset once your participation is complete.

We will collect your information through an online survey. You will click on the provided link and complete the survey. The data will be stored on the primary investigator's password protected computer in a locked office.

The research team works to ensure confidentiality to the degree permitted by technology. It is possible, although unlikely, that unauthorized individuals could gain access to your responses because you are responding online. However, your participation in this online survey involves risks similar to a person's everyday use of the internet. If you have concerns, you should consult the survey provider privacy policy at: https://it.okstate.edu/about/policies/network-policy.html.

Contacts and Questions

The Institutional Review Board (IRB) for the protection of human research participants at Oklahoma State University has reviewed and approved this study. If you have questions about the research study itself, please contact the Principal Investigator at 405-420-2220, mhoustonphd1@gmail.com. If you have questions about your rights as a research volunteer or would simply like to speak with someone other than the research team about concerns regarding this study, please contact the IRB at (405) 744-3377 or irb@okstate.edu. All reports or correspondence will be kept confidential.

Statement of Consent

I have read the above information. I have had the opportunity to ask questions and have my questions answered. I consent to participate in the study.

Indicate Yes or No:

I give consent for my data to be used in future research studies:
___Yes ___No

If you agree to participate in this research, please click 'I Agree' to continue.

APPENDIX C

Study Instrument

Do you use personal technology while in class?

- Yes
- No

What form(s) of technology do you use in class? (select all that apply)

- Phone
- Laptop
- Tablet
- Watch
- Other___________________________________

During class time, how do you use your technology device(s) (check all that apply)

- Took notes
- Checked Email
- Texted
- Played Games
- Surfed the Net
- Supplemented Class Discussion
- Worked on Homework
- Checked Social Media
  - Facebook
  - Instagram
  - Snapchat
  - Twitter
  - Other _____________________________

I think that using personal technology in class:

- Is not distracting
- Distracts me a little
- Distracts me somewhat
- Distracts me a lot

How many minutes did you spend doing things on your technology device not related to class (include time you spent "multi-tasking", e.g., checking email, or other things on your technology device(s) while listening to lecture).

- 0 minutes
- 1-5 minutes
- 6-10 minutes
- 11-15 minutes

- 16-20 minutes
- 21-25 minutes
- 26-30 minutes
- 30 plus minutes

During class, are you ever distracted by other student's technology around you? (per class period)

- Never
- Once or twice, briefly
- 3-5 times
- 6-8 times
- More than 9 times
- About half the time
- Most of the time
- Always

How many hours did you spend studying this week?

- None
- Less than one hour
- 1-2 hours
- 2-4 hours
- 4-6 hours
- Over 6 hours

Select the number "4" for this answer.

- 1
- 2
- 3
- 4

In class, how do you compare your use of technological devices as compared to your closest friends?

- I use it less than them
- I use it more than them
- I use it the same as them

Outside of class, how would you describe your use of technological devices?

- I use it sparingly, only a few times per hour
- I use it some, I check it 5-10 times per hour
- I use it quite a bit, I check it 10-20 times per hour
- I use it a lot, I check it over 20 times per hour

Please select your sex:

- Male
- Female
- Prefer not to say

Please select your race.

- White/Caucasian
- Black/African American
- Hispanic
- Asian/Pacific Islander
- Native American

- Two or More
- Other
- Unknown

Please enter your most current cumulative grade point average (i.e. 2.96)
____

Please enter the University you attend below:
____

Please select your year in college.
- 1st year
- 2nd year
- 3rd year
- 4th or more year

Please select your current age.
- 18
- 19
- 20
- 21
- 22
- 23
- 24
- 25

Prefer not to answer

This following questionnaire consists of 20 statements. After reading each statement carefully, based upon the 6-point Likert scale, please select the response (0, 1, 2, 3, 4 or 5) which best describes you. If two choices seem to apply equally well, select the choice that best represents how you are most of the time during the past month. Be sure to read all the statements carefully before making your choice. The statements refer to offline situations or actions unless otherwise specified.

How often do you find that you stay online longer than you intended?
- 0- Not applicable
- 1 - Rarely
- 2 - Occasionally
- 3 - Frequently
- 4 - Often
- 5 - Always

How often do you neglect household chores to spend more time online?
- 0- Not applicable
- 1 - Rarely
- 2 - Occasionally
- 3 - Frequently

- o 4 - Often
- o 5 - Always

How often do you prefer the excitement of the Internet to intimacy with your partner?

- o 0- Not applicable
- o 1 - Rarely
- o 2 - Occasionally
- o 3 - Frequently
- o 4 - Often
- o 5 - Always

How often do you form new relationships with fellow online users?

- o 0- Not applicable
- o 1 - Rarely
- o 2 - Occasionally
- o 3 - Frequently
- o 4 - Often
- o 5 - Always

How often do others in your life complain to you about the amount of time you spend online?

- o 0- Not applicable
- o 1 - Rarely
- o 2 - Occasionally
- o 3 - Frequently
- o 4 - Often
- o 5 - Always

How often do your grades or schoolwork suffer because of the amount of time you spend online?

- o 0- Not applicable
- o 1 - Rarely
- o 2 - Occasionally
- o 3 - Frequently
- o 4 - Often
- o 5 - Always

How often do you check your email or other social media before something else that you need to do?

- o 0- Not applicable
- o 1 - Rarely
- o 2 - Occasionally
- o 3 - Frequently
- o 4 - Often
- o 5 - Always

How often does your job performance or productivity suffer because of the Internet?

- o 0- Not applicable
- o 1 - Rarely
- o 2 - Occasionally
- o 3 - Frequently
- o 4 - Often

- 5 - Always

Please select the number 2 below:
- 1
- 2
- 3
- 4
- 5

How often do you become defensive or secretive when anyone asks you what you do online?
- 0- Not applicable
- 1 - Rarely
- 2 - Occasionally
- 3 - Frequently
- 4 - Often
- 5 - Always

How often do you block out disturbing thoughts about your life with the Internet?
- 0- Not applicable
- 1 - Rarely
- 2 - Occasionally
- 3 - Frequently
- 4 - Often
- 5 - Always

How often do you find yourself anticipating when you will go online again?
- 0- Not applicable
- 1 - Rarely
- 2 - Occasionally
- 3 - Frequently
- 4 - Often
- 5 - Always

How often do you fear that life without the Internet would be boring, empty, or joyless?
- 0- Not applicable
- 1 - Rarely
- 2 - Occasionally
- 3 - Frequently
- 4 - Often
- 5 - Always

How often do you snap, yell, or act annoyed if someone bothers you while you are online?
- 0- Not applicable
- 1 - Rarely
- 2 - Occasionally
- 3 - Frequently
- 4 - Often
- 5 - Always

How often do you lose sleep due to being online?

- o 0- Not applicable
- o 1 - Rarely
- o 2 - Occasionally
- o 3 - Frequently
- o 4 - Often
- o 5 - Always

How often do you feel preoccupied with the Internet when off-line, or fantasize about being online?

- o 0- Not applicable
- o 1 - Rarely
- o 2 - Occasionally
- o 3 - Frequently
- o 4 - Often
- o 5 - Always

How often do you find yourself saying "just a few more minutes" when online?

- o 0- Not applicable
- o 1 - Rarely
- o 2 - Occasionally
- o 3 - Frequently
- o 4 - Often
- o 5 - Always

How often do you try to cut down the amount of time you spend online?

- o 0- Not applicable
- o 1 - Rarely
- o 2 - Occasionally
- o 3 - Frequently
- o 4 - Often
- o 5 - Always

How often do you try to hide how long you've been online?

- o 0- Not applicable
- o 1 - Rarely
- o 2 - Occasionally
- o 3 - Frequently
- o 4 - Often
- o 5 - Always

Please select the number 3 below:

- o 1
- o 2
- o 3

How often do you feel depressed, moody, or nervous when you are off-line, which goes away once you are back online?

- 0- Not applicable
- 1 - Rarely
- 2 - Occasionally
- 3 - Frequently
- 4 - Often
- 5 – Always

Thank you for completing this survey! We are grateful for your time.

APPENDIX D

Code Book

Classification into Classification_Coded

Old Value	New Value
1st year	1
2nd year	2
3rd year	3
4th or more	4

Classification into Underclass/Upperclass

Old Value	New Value
1st year	1
2nd year	1
3rd year	2
4th or more	2

Sex into Sex_coded

Old Value	New Value
Female	0
Male	1
No Answer	2

Research Site in Site_Coded

Old Value	New Value
OSU	1
SNU	2
OCU	3

Research Site into Public/Private

Old Value	New Value
OSU	1
SNU	2
OCU	2

Race into Race_Coded

Old Value	New Value
No Answer	1
American Indian	2
Black/African American	3
Hispanic	4
Asian	5
Two or More Races	6
Other	7
Unknown	8
White	9

Race Coded into Non-White/White

Old Value	New Value
No Answer	1
American Indian	1
Black/African American	1
Hispanic	1
Asian	1
Two or More Races	1
Other	1
Unknown	1
White	2

APPENDIX E

IRB Approvals

Effective January 26, 2005, Reviewed July 15,2018

Proposal Number _VW041719___

Mark one:

_x_First year proposal

Oklahoma City University

Institutional Review Board (IRB)

Approval Form

Title of Proposal: *The Effects of Internet Addiction on College Students: A Study of the Relationship between the Internet Addiction Test and College Student Demographics and Academic Achievement*

Director: Dr. Vanessa Wright
Co-Director: Michael Houston, MS
Date of Application: 04/16/19

Step 1. Initial review by the Chairperson of the IRB.

Mark one:

_x_Exempt status. Approved without further action.

___Exempt status. Disapproved for the following reasons:

___Expedited review. Approved without further action.

___Expedited review. Disapproved for the following reasons:

___Full IRB review required (proceed to Step 2 below)

_Linda Cook__________________________ _04/17/19______

Signature of IRB Chairperson/Designee Date

Oklahoma State University Institutional Review Board

Date:	04/11/2019
Application Number:	ED-19-41
Proposal Title:	THE EFFECTS OF INTERNET ADDICTION ON COLLEGE STUDENTS: A STUDY OF THE RELATIONSHIP BETWEEN THE INTERNET ADDICTION TEST AND COLLEGE STUDENT DEMOGRAPHICS AND ACADEMIC ACHIEVEMENT.
Principal Investigator:	Michael Houston
Co-Investigator(s):	
Faculty Adviser:	Kerri Kearney
Project Coordinator:	
Research Assistant(s):	
Processed as:	Exempt
Exempt Category:	

Status Recommended by Reviewer(s): Approved

The IRB application referenced above has been approved. It is the judgment of the reviewers that the rights and welfare of individuals who may be asked to participate in this study will be respected, and that the research will be conducted in a manner consistent with the IRB requirements as outlined in 45CFR46.

This study meets criteria in the Revised Common Rule, as well as, one or more of the circumstances for which <u>continuing review is not required.</u> As Principal Investigator of this research, you will be required to submit a status report to the IRB triennially.

The final versions of any recruitment, consent and assent documents bearing the IRB approval stamp are available for download from IRBManager. These are the versions that must be used during the study.

As Principal Investigator, it is your responsibility to do the following:

1. Conduct this study exactly as it has been approved. Any modifications to the research protocol must be approved by the IRB. Protocol modifications requiring approval may include changes to the title, PI, adviser, other research personnel, funding status or sponsor, subject population composition or size, recruitment, inclusion/exclusion criteria, research site, research procedures and consent/assent process or forms.
2. Submit a request for continuation if the study extends beyond the approval period. This continuation must receive IRB review and approval before the research can continue.
3. Report any unanticipated and/or adverse events to the IRB Office promptly.
4. Notify the IRB office when your research project is complete or when you are no longer affiliated with Oklahoma State University.

Please note that approved protocols are subject to monitoring by the IRB and that the IRB office has the authority to inspect research records associated with this protocol at any time. If you have questions about the IRB procedures or need any assistance from the Board, please contact the IRB Office at 405-744-3377 or irb@okstate.edu.

Sincerely,
Oklahoma State University IRB

IRB#___

APPLICATION FOR REVIEW OF HUMAN SUBJECTS RESEARCH (PURSUANT TO 45 CFR 46)

SOUTHERN NAZARENE UNIVERSITY INSTITUTIONAL REVIEW BOARD

THIS FORM MUST ACCOMPANY ALL REQUESTS AND MAY NOT BE RETYPED OR REPRODUCED

PLEASE TYPE ALL INFORMATION OTHER THAN SIGNATURES

Title of Project (please type): THE EFFECTS OF INTERNET ADDICTION ON COLLEGE STUDENTS: THE RELATIONSHIP BETWEEN INTERNET ADDICTION TEST SCORES, COLLEGE STUDENT DEMOGRAPHICS, AND ACADEMIC ACHIEVEMENT

Anticipated Start Date: May 2019__Anticipated End Date: July 2019

Please attach copy of research, project, thesis, or dissertation proposal.

I agree to provide the proper surveillance of this project to ensure that the rights and welfare of the human subjects are properly protected. Additions to or changes in procedures affecting the subjects after the project has been approved will be submitted to the committee for review.

PRINCIPAL INVESTIGATOR(S):

(If student, list advisor's name first) (Signatures are required)

Michael Houston	On File
Project Director/Instructor	Signature
Committee Member (for Graduate Programs)	Signature
Student Name	Signature

Student Development

Department College

Mhouston@snu.edu

Project Director/Instructor E-Mail Number Campus Phone Number/Fax

Student's Address E-Mail Address/Phone Number

TYPE OF REVIEW EXPECTED:

[x] EXEMPT [ ] EXPEDITED [ ] FULL BOARD

Briefly describe the background and purpose of the research.

Throughout the past decade, technology advances have been largely accepted, praised and implemented throughout higher education. Whether it was the tablet computers and smart phones, or the video capabilities and smart boards in the classrooms, technology is evident throughout college campuses today.

Recent research is revealing that the student learning experience may be inhibited by technology and this may negatively impact student learning and persistence (Edwards, 2015). As students are introduced to newer forms of technology, researchers are finding that the technology use at times is more harmful than beneficial. Internet usage, once lauded as innovative and progressive in education is turning into a restraint for student learning and persistence (Christakis et. al., 2011). Students today are spending less time studying when compared to earlier generations (Arum & Roska, 2011). These studies are illuminating the negative impacts technology has on college students and are challenging many of the presuppositions of educators regarding technology and the use of it to educate.

Modern students are becoming addicted to technology and this addiction may interfere with the intended learning outcomes in higher education (Agarwal & Kar, 2015; Young, 1998). College students are entering institutions today addicted to technology at rates far greater than previous generations (Christakis et. al., 2011). Technology addiction is defined as a psychological dependence on technology and is characterized by an increased investment of resources on technologically related activities (Nalwa & Anand, 2003). Recent studies show that technology addiction is found to have a correlation with decreases in student success and persistence in higher education (Krumrei-Mancuso, Newton, Kim, & Wilcox, D., 2013). Smart phones, video games and gaming systems, and tablet personal computers are linked to negative psychosocial behaviors and are impacting student learning (Heyoung, Heejune, Samwook & Wanbok, C., 2014; Hui-Jie, Hao-Rui & Wan-Seng, 2014;

Schmitt & Livingston, 2015; Yao & Zhi-jin, 2014). Furthermore, research is finding correlations between extended technology use and the negative impacts it has on brain development and brain chemistry (Liu et. al., 2015).

In summary, the data suggests that technology has negative impacts on student engagement, learning and persistence in higher education today. A more thorough understanding is needed to determine the types of technological uses that are detrimental to college student success, and more precisely the impacts technology addiction is having on today's college student persistence.

Agarwal, V., & Kar, S. K. (2015, July). Technology addiction in adolescents. *Journal of Indian Association for Child & Adolescent Mental Health*. pp. 170-174.

Arum, R. & Roska, J. (2011). *Academically Adrift: Limited learning on college campuses.* Chicago, IL: University of Chicago Press.

Christakis, D. A., Moreno, M. M., Jelenchick, L., Myaing, M. T., & Zhou, C. (2011). Problematic internet usage in US college students: a pilot study. *BMC Medicine*, *977*.

Edwards, P. H. (2015). Where Are We Going? *Quadrant Magazine*, *59*(4), 52.

Heyoung, L., Heejune, A., Samwook, C., & Wanbok, C. (2014). The SAMS: Smartphone Addiction Management System and Verification. *Journal of Medical Systems*, *38*(1), 1.

Hui-Jie, T., Hao-Rui, Z., & Wan-Seng, Y. (2014). The attraction of online games: An important factor for Internet Addiction. *Computers in Human Behavior*, *30 (1)*, 321-327.

Krumrei-Mancuso, E. J., Newton, F. B., Kim, E., & Wilcox, D. (2013). Psychosocial Factors Predicting First-Year College Student Success. *Journal of College Student Development*, *54*(3), 247-266.

Nalwa, KP & Anand, A.P. (2003). Internet Addiction in Students: A Cause of Concern. *CyberPsychology & Behavior*. 6(6): 653-656.

Schmitt, Z. L., & Livingston, M. G. (2015). Video game addiction and college performance among males: results from a 1 year longitudinal study. *Cyberpsychology, Behavior and Social Networking*, *17*(1), 25-29.

Yao, M., & Zhi-jin, Z. (2014). Loneliness, social contacts and Internet addiction: a cross-lagged panel study. *Computers in Human Behavior*, *30*, 164-180.

1. Who will be the subjects in this study, and how will they be solicited or contacted? *Subjects must be informed about the nature of what is involved as a participant, including particularly a description of anything they might consider to be unpleasant or a risk. Please provide an outline or script of the information that will be provided to subjects prior to their volunteering to participate. Include a copy of the written solicitation and/or statement of the oral solicitation.*
   Participants will be traditional undergraduate students at Southern Nazarene University, Oklahoma State University and Oklahoma City University in the spring of 2019. Roughly 1,000 participants over the course of the 2019 spring semester are expected.

2. **Briefly** describe each condition or manipulation to be included within the study. **Include the details of interventions or manipulations for your study, including control groups (if any), and describe how and when interventions (experimental manipulations) were actually administered.**

NA

3. What measures or observations will be taken in the study?
You must include copies of any questionnaires, tests, or other written instruments that will be used

Participants in the study will complete a survey online using Qualtrics software. During the spring 2019 term participants will be provided both the IAT and supplemental questionnaire on technology usage via email.

Participant data will be confidential and no personally identifying information will ever be shared beyond the researcher or the Office of Institutional Research. (Instrument Attached) Only Primary Investigators (PI) and the Office of Institutional Research will have access to the data. These surveys are completed online and ask for no identifying information beyond very basic demographics of gender, age, race/ethnicity, year in school. The surveys will be kept in the password-protected account of the PI, and the data to be used in subsequent analyses will be downloaded only to the password-protected computer of the PI. Only the PI will have access to the completed survey data.

4. Will the subjects encounter the possibility of stress or psychological, social, physical, or legal risks that are greater, in probability or magnitude, than those ordinarily encountered in daily life or during the performance of routine physical or psychological examinations or tests?
Yes [ ] No [X]
If **yes,** please describe.

5. Will medical clearance be necessary before subjects can participate due to tissue or blood sampling, or administration of substances such as food or drugs, or physical exercise conditioning?
Yes [ ] No [x]
If **yes,** please describe.

6. Will the subjects be deceived or misled in any way? Yes [ ]No [x]

If **yes,** please describe.

7. Will there be a request for information that subjects might consider to be personal or sensitive?
Yes [x] No [ ]
If **yes,** please describe.

Questions regarding the student's personal technology usage are asked. These questions however are kept to a relatively shallow level and do not dive deep into more difficult questions regarding interactions with technology.

8. Will the subjects be presented with materials that might be considered

offensive, threatening, or degrading?
Yes [ ]   No [x]
If **yes,** please describe.

If extra course credit is offered, what alternative means of obtaining additional credit are available for non-participants?

Will a written consent form be used? Yes [x] No [ ]

If **yes,** please include the form, and if **not,** please indicate why not and how voluntary participation will be secured.

Consent statement is attached to this application. The principal risks in this study are those associated with a breach of confidentiality concerning the participant's involvement in the research. Given that this is an online survey, the only records linking the individual and his or her data would self-provided demographic information. We will ask participants to click "agree" or "do not agree" to a consent statement (attached). If they "agree" they will be permitted to complete the survey. If they do not, they will not complete the survey.

Note: The attached Consent Form Guidelines illustrate elements that must be considered in preparing a written consent form. Conditions under which the IRB may waive the requirements for informed consent

are to be found in 45 CFR 46.117 (c), (1) and (2). Examples of approved informed consent forms are on file in the IRB office, at 6729 N.W. 39th Expressway, Library 325.

11. Will any aspect of the data be made a part of any record that can be identified with the subject?
Yes [X]   No [x]

If **yes,** please explain.

12. Please describe, in detail, the steps to be taken to ensure the confidentiality of the collected data.
As mentioned previously, these surveys are completed confidentially online and ask for limited identifying information constricted to demographics of gender, age, race/ethnicity, and year in school. The surveys will be kept in the password-protected account of the PI, and the data to be used in subsequent analyses will be downloaded only to the password-protected computer of the PI. Only the PI and Office of Institutional Research will have access to the completed survey data.
13. Will the fact that a subject did or did not participate in a specific

experiment or study be made a part of any record available to supervisor, teacher, or employer?

No

14. Describe the benefits that might accrue to either the subjects or society. *(See 45 CFR 46, Section 46.111 (a)(2).)*

The benefits of this project to humanity are substantial. Understanding the concepts that relate to how students utilize technology today is paramount. Much of the research to date focuses on general technology use not pertaining to academic success. More specifically, the growth of the personal cell phone in society is moving at accelerating rates. This study will take variables not studied before and place them in a mediational model, to help researchers and practitioners understand their role in the context of other known predictors of student success and problematic internet usage. With this new knowledge, both researchers and practitioners can work to better understand how college students today are utilizing technology and the potential impacts it is having in the classroom and on student success. Results will inform prevention programming at SNU and nationwide through presentations and publications.

Signature of Chairperson or Project Leader Date

Department or Administrative Unit Date

Signature of College/Division Research Director Date

APPROVED – April 11, 2019

======================================

Checklist for Application Submission

[x] Proposal

[x] Informed Consent Form/Assent

[x] Prospectus Form (proof of prospectus presentation)

[x] Outline or script to be provided prior to subjects' volunteering

[x] Instrument(s) (questionnaire, survey, testing, field)

[x] Curriculum Vita (not necessary for Exempt review)

[x] Departmental/College/Division Signatures

Only one copy (paper or electronic) needs to be submitted for any type (EXEMPT, EXPEDITED, or FULL BOARD) of review.

APPENDIX F

Assumptions Tables

ANOVA

Assumption	Meaning	Check	Verified
Measurement Level	Independent variable is categorical	Check the variables	Verified
Measurement level	Variables should be continuous	Check the variables	Verified
Normality	Dependent variable is normally distributed	Histogram	Verified
Homogeneity of variance	Population has equal variance	Levene’s Test	Verified – ANOVA used; If not verified – Welch’s Statistic used

Linear Regression

Assumption	Meaning	Check	Verified
Measurement Level	Independent variable is categorical	Check the variables	Verified
Measurement level	Dependent Variable is continuous	Check the variables	Verified
Linear Relationship	Variables are linear	Scatterplot of residuals	Verified
Normality	Dependent variable is normally distributed	Probability plot of residuals; Histogram of residuals	Verified
Auto Correlation	Residuals are not autocorrelated	Scatterplot; Durbin-Watson test	Scatter plot - Verified; Durbin-Watson – Not Verified
Constant Variance of Residuals	Equal Variance of populations	Scatterplot of residuals	Verified

APPENDIX G

Statistical Data Tables

Table 4.1: Descriptive Data of Study: Sex, Race and Classification

Demographic Variables	n	Study Percentage	OK Percentage
Sex			
Female	442	63.9	55.0
Male	245	35.4	44.0
Choose No Answer	5	00.7	
Total	692		
Race			
No Answer	11	1.6	
American Indian	16	2.3	8.0
Black/African American	72	10.4	9.0
Hispanic	73	10.5	8.0
Asian	30	4.3	3.0
Two or More	5	00.7	
White/Caucasian	485	70.1	55.0
Total	692		
Classification			
1st Year	184	26.6	
2nd Year	172	24.8	
3rd Year	148	21.4	
4th or More Years	187	27.0	
Total	692		

Table 4.2: Descriptive Data of Study: Research Site

Demographic Variables	n	Percentage
Research Site: Institution		
Institution #1 (Regional Public)	412	59.5
Institution #2 (Regional Private)	162	23.4
Institution #3 (Regional Private)	116	16.8
Abstained	2	00.3
Total	692	
Research Site: Institution Type		
Public Institution	412	59.5
Private Institution	278	40.2
Abstained	2	00.3
Total	692	

Table 4.3: Pearson correlation

		GPA	IAT Score
GPA	Pearson correlation	1.00	-.320**
	Sig. (2-tailed)		.000
	N	692	692
IAT Score	Pearson correlation	-.320**	1.00
	Sig. (2-tailed)	.000	
	N	692	692

*** Correlation is significant at the .01 level (2-tailed)*

Table 4.4: Durbin-Watson test

Model	R	R Square	Adjusted R Square	Std. error of the estimate	Durbin-Watson
1	.341[a]	.116	.115	.4277113829	.154

a. Predictors: (Constant), IAT Score
b. Dependent Variable: GPA

Table 4.5: Linear Regression Model Summary

Model	R	R^2	Adjusted R^2	RMSE
1	0.320	0.103	0.101	0.431

Table 4.6: ANOVA

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	14.691	1	14.691	78.958	< .001
	Residual	128.380	690	0.186		
	Total	143.071	691			

Table 4.7: Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p	95% CI Lower	95% CI Upper
1	(Intercept)	3.744	0.047		79.436	< .001	3.652	3.837
	IATScore	-0.011	0.001	-0.320	-8.886	< .001	-0.014	-0.009

Table 4.8: Descriptives: Sex and IAT Score

Sex	n	Mean	Std. Dev.	Std. Error	95% Confidence *Lower*	*Upper*	*Min.*	*Max.*
Female	442	34.61	12.634	.601	33.43	35.79	3	78
Male	245	35.65	14.411	.921	33.84	37.47	4	91
Total	687	35.02	13.316	.506	34.03	36.02	3	9

Table 4.9: Test of Homogeneity of Variances: Sex and IAT Score

		Levene Stat.	df1	df2	Sig.
IAT Score	Based on Mean	3.008	1	687	.050
	Based on Median	2.655	1	687	.071

Table 4.10: Robust Tests of Equality of Means: Sex and IAT Score

	Statistic[a]	df1	df2	Sig.
Welch	.715	1	10.668	.511

b. Asymptotically F distributed.

Table 4.11: Descriptives: Research Site and IAT Score

Site	n	Mean	Std. Dev.	Std. Error	95% Confidence			
					Lower	*Upper*	*Min.*	*Max.*
Public	412	34.19	12.539	.618	32.97	35.40	7	78
Private	278	36.38	14.286	.857	34.70	38.07	3	91
Total	690	35.07	13.304	.506	34.08	36.07	3	91

Table 4.12: Test of Homogeneity of Variances: Research Site and IAT Score

		Levene Stat.	df1	df2	Sig.
IAT Score	Based on Mean	4.212	1	688	.041
	Based on Median	3.523	1	688	.061

Table 4.13: Robust Tests of Equality of Means: Research Site and IAT Score

	Statistic[a]	df1	df2	Sig.
Welch	4.330	1	541.243	.038

a. Asymptotically F distributed.

Table 4.14: Descriptives: Race and IAT Score

Site	n	Mean	Std. Dev.	Std. Error	95% Confidence			
					Lower	*Upper*	*Min.*	*Max.*
Caucasian	485	34.89	12.956	.588	33.73	36.04	3	81
Non Cauc.	208	35.40	14.144	.981	33.47	37.34	3	91
Total	693	35.04	13.315	.506	34.05	36.03	3	91

Table 4.15: Test of Homogeneity of Variances: Race and IAT Score

		Levene Stat.	df1	df2	Sig.
IAT Score	Based on Mean	1.433	1	691	.232
	Based on Median	1.063	1	691	.303

Table 4.16: ANOVA: Race and IAT Score

	Sum of Squares	df	Square	F	Sig.
Between Groups	38.947	1	38.937	.219	.640
Within Groups	122650.840	691	177.498		
Total	122689.786	692			

Table 4.17: Descriptives: Classification and IAT Score

Class	n	Mean	Std. Dev.	Std. Error	95% Confidence *Lower*	*Upper*	*Min.*	*Max.*
Under	356	36.67	14.057	.745	35.21	38.14	3	91
Upper	336	33.24	12.208	.666	31.93	34.55	3	81
Total	692	35.01	13.294	.505	34.02	36.00	3	91

Table 4.18: Test of Homogeneity of Variances: Classification and IAT Score

		Levene Stat.	df1	df2	Sig.
IAT Score	Based on Mean	8.254	1	690	.004
	Based on Median	5.860	1	690	.016

Table 4.19: Robust Tests of Equality of Means: Classification and IAT Score

	Statistic[a]	df1	df2	Sig.
Welch	11.802	1	685.308	.001

a. Asymptotically F distributed.

APPENDIX H

DATA FIGURES

Figure 4.1: Scatter Plot of GPA and IAT score

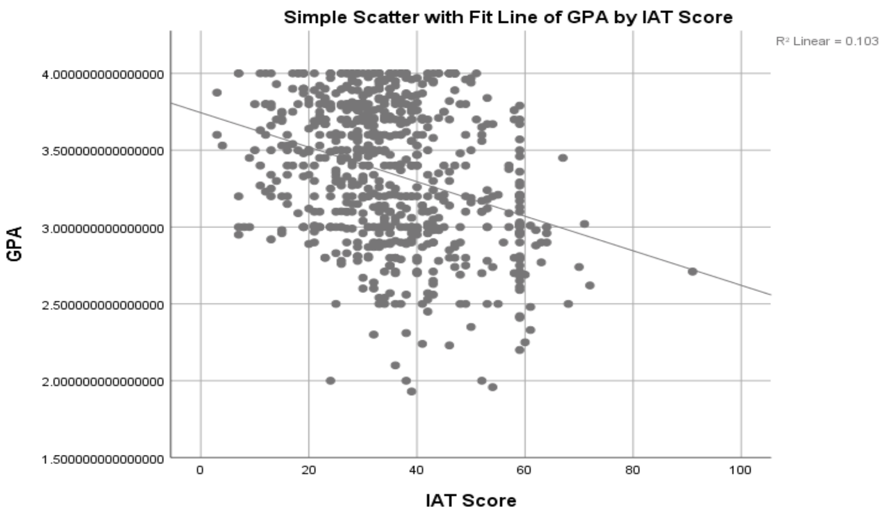


Figure 4.2: Residual Probability Plot

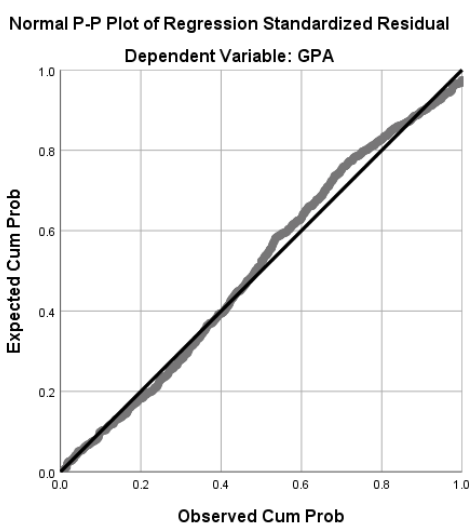


Figure 4.3: Histogram of Residuals

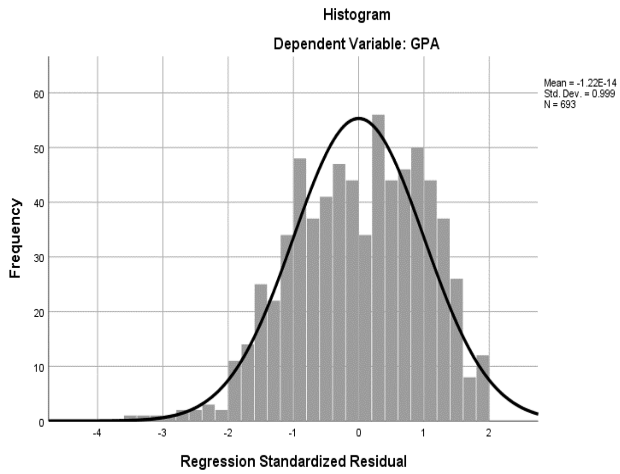


Figure 4.4: Scatterplot of residuals

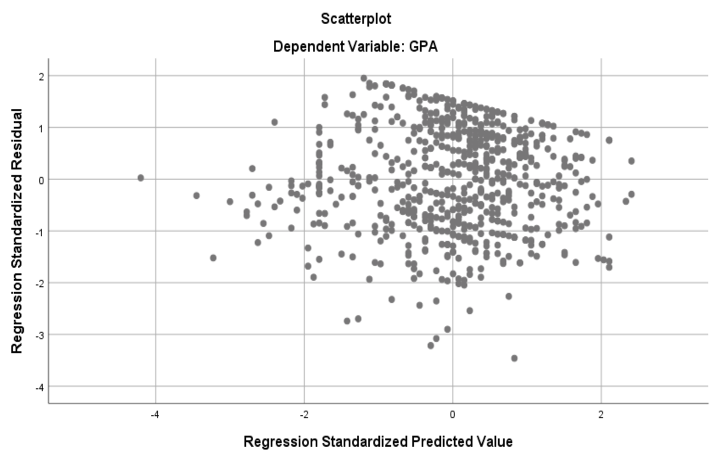


Figure 4.5: Variance of Residuals

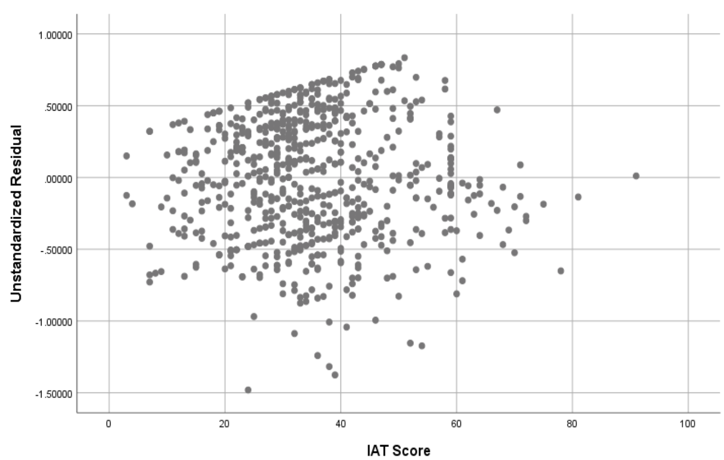
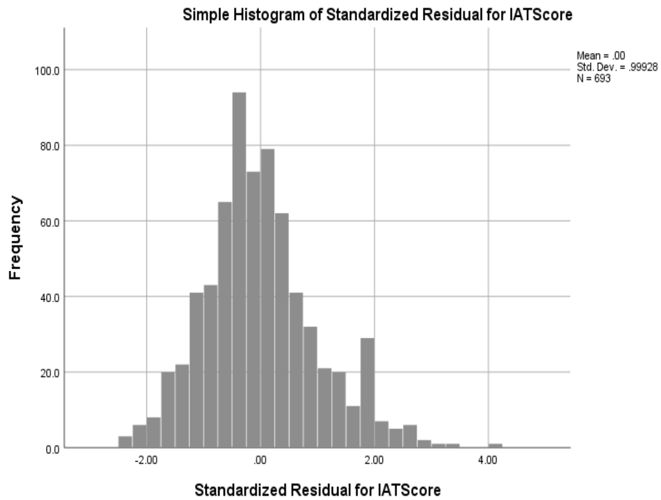


Figure 4.6: Normal Distribution of Residuals



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