INVESTIGATING YOUNG ADULT CELL PHONE USE: IMPLICATIONS FOR SLEEP QUALITY, ACADEMIC PERFORMANCE, AND PSYCHOLOGICAL WELL-BEING

A Dissertation

by

SURESH CHANDRA JOSHI

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Co-Chair of Committee,	Steven Woltering
Co-Chair of Committee,	Robert Woodward
Committee Members,	Jeffrey Liew
	Rhonda N. Rahn
Head of Department,	Fuhui Tong

December 2020

Major Subject: Educational Psychology

ABSTRACT

The primary aim of this dissertation was to investigate the impact of cell phone use (CPU) on sleep quality, academic performance, and the psychological well-being (PWB) of young adults. This goal was achieved by 1) examining the relationship between undergraduate students' CPU and the sleep quality components, i.e., sleep latency and sleep difficulty, 2) examining the relationship between CPU and academic performance (GPA) of undergraduate students, and 3) investigating the relationship between CPU and PWB of undergraduate students.

A sample of 525 undergraduate students (75.4% female) at Texas A&M University participated in the study during fall 2019. The data was collected using a validated self-reported quantitative questionnaire. Concerning the first research question, ordinal logistic analyses indicated that there were higher odds of sleep latency occurring with the exposure to the use of cell phones for unstructured leisure activities before sleep (CPU_BeforeBed). Ordinal logistic analyses also indicated that there were higher odds of sleep difficulty occurring when undergraduate students assessed sexually explicit, violent, or emotionally charged media content using cell phones before sleep (CPU_Arousal). As for my second research question, nonparametric correlational analysis showed that the frequency of CPU during a class/lecture, lab, and/or study session (CPU_Switch) was negatively correlated to the GPA of undergraduate students. However, the use of cell phones for self-regulated learning strategies (CPU_SRLBehavior) was unrelated to the academic performance of undergraduate

students, as determined by nonparametric correlational analysis. Finally, for the third research question, there were higher odds of PWB occurring with both cell phone social media feeling (CPU_SMF) and cell phone social media response (CPU_SMR) of undergraduate students, as determined by ordinal logistic.

Findings suggested that CPU_BeforeBed adversely affects the sleep latency of undergraduate students, more frequently that of females than males. Findings also suggested that CPU_Arousal affects the sleep difficulty of undergraduate students badly, with a higher occurrence of the impact in male undergraduate students. Switching between cell phones and academic tasks during a class/lecture, lab, and/or study session affects the academic performance of undergraduate students negatively, with no statistically significant difference in the occurrence of impact in male and female undergraduate students. However, using cell phones for self-regulated learning strategies does not affect academic performance. The use of cell phones for social media feelings and the use of cell phones for social media responses help undergraduate students improve their PWB, with no statistically significant difference in the occurrence of impact in male and female undergraduate students. CPU_BeforeBed predicted sleep latency and CPU_Arousal predicted the sleep difficulty of undergraduate students. CPU_Switch was not found as a significant predictor of the GPA of undergraduate students. Lastly, CPU_SMF strongly predicted the PWB of undergraduate students. However, CPU_SMR of undergraduate students did not predict their PWB.

DEDICATION

To

Mum, Num, and Shum

(Nicknames of my wife Kalpana, daughter Kaatyayani, and my son Aaditya)

for their countless hours and days I have stolen during completion of this degree.

ACKNOWLEDGEMENTS

The Almighty has been kind for providing me the opportunity to go back to graduate school after spending almost seventeen years in the workplace. Partly, I thank the Fulbright Distinguished Award in Teaching Program scholarship, which I received in 2012, for allowing me to continue my education. It was the Fulbright that gave me the courage to quit my job at the age of 42, leaving my family with a pre-teen daughter (ten-years-old) and an infant son (six months), and travel to a country half-way around the world to further my education. Fulbright tenure strengthened my belief in learning and broadened my perspective of education. The Fulbright scholarship indeed transformed my life.

Texas A&M also greatly influenced my decision to go back to school. I am thankful and gracious to God for creating institutions like Texas A&M that allowed me to further my education. I would like to acknowledge my committee, which one of my committee members once called a "tough committee." This committee has taught me how to think and analyze critically and write clearly. I am tremendously fortunate to have the committee members Dr. Steven Woltering, Dr. Jay Woodward, Dr. Jeffrey Liew, and Dr. Rhonda Rahn. I am appreciative of my co-chairs, Dr. Woltering and Dr. Woodward, who assisted me with my dissertation and brought a depth of knowledge that few could match. They offered an amazing amount of support for this project and gave thoughtful feedback that always aimed at helping me learn new things. I am thankful to Dr. Liew for the feedback he provided at each developmental stage of my dissertation, especially during finalizing the instrument and developing the theoretical framework of the study. I am also thankful to Dr. Rahn for reviewing the manuscripts so closely at every stage of my dissertation and for her comments on the study instrument, the significance, and relevance of the study to practical life.

My journey throughout graduate school could not have been so productive and enjoyable without the involvement of Texas A&M's University Writing Center (UWC). During 140 writing sessions and 6 Dissertation Article and Thesis Assistance sessions (ten writing sessions each) at the UWC, I learned to write clearly and concisely. I owe my writing development to the UWC, and I express my deepest gratitude to each individual at the UWC for working closely to make my manuscript readable/understandable. My colleagues from the workplace, Texas Center for the Advancement of Literacy and Learning, where I served as a Graduate Assistant for almost four years, deserve my compliments as well for providing a fruitful learning environment, especially through stressful times during the completion of my degree.

I would like to acknowledge Dr. Shuling Liu from the Department of Statistics at Texas A&M for her guidance on the statistical analysis of my dissertation. Dr. Liu’s direction has been tremendously helpful during the data analysis phase of my dissertation and I appreciate the time she invested in me. The discussion of my graduate journey cannot be completed without the mention of Dr. Susan Pedersen, my first supervisor at the Department of Educational Psychology at Texas A&M. I thank Dr. Pedersen for the support she provided during the first year of my degree program.

Finally, staying away from family would not have been possible for me without the constant mental, emotional, and psychological support of my wife, Kalpana Joshi. She took care of our kids as a single parent when I left home for graduate school. I thank her for everything she did for letting me complete my degree. I also acknowledge the patience and unconditional love from my daughter, Kaatyayani Joshi, and son, Aaditya Joshi, whose precious and countless hours and days I have stolen in due course of completing my dissertation. I also take this opportunity to thank my brother and his family, my relatives, peers, and all others for their love and support. Finally, I thank my parents for bringing me into this world and raising me as a person capable of making grand choices in life.

NOMENCLATURE

CPU	Cell phone use
CPUsers	Cell phone users
GPA	Grade point average (Academic performance)
PSQI	Pittsburgh Sleep Quality Index
PWB	Psychological well-being
CPMC	Cell-phone-mediated-communication
CPU_Total	Total hours-per-day spent using cell phones
CPU_BeforeBed	The use of cell phone before sleep
CPU_Arousal	The use of cell phones for accessing sexually explicit, violently, or emotionally charged media content
CPU_Switch	The frequency of cell phone use during a class/lecture, lab and/or study session
CPU_SRL	The use of cell phones for self-regulated learning strategies
CPU_SMF	The use of cell phones for social media feeling
CPU_SMR	The use of cell phones for social media response

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1. Availability and functionality of cell phones in the information age

Mobile phones, often called cellular phones or cell phones, are compact handheld electronic devices meant for voice communication. Technological advancements from the last two decades accelerated the growth of these devices in such a way that "most mobile phones provide voice communications, short message service (SMS), multimedia message service (MMS), and newer phones may also provide internet services such as Web browsing, instant messaging capabilities and e-mail" (Beal, 2008). With these capabilities, current mobile phones, labeled as cell phones throughout this study, can be used for various purposes including entertainment, information gathering, and social interaction.

Abundant, user-friendly educational applications make cell phones useful learning tools for a digital generation, particularly for "those between the age of 18 and 29," the age range defined for young adults by the PEW Research Center (2011). The vast functionality of these tools for information gathering and social networking compel young adults to be constant users of these devices. While the availability of information makes a cell phone a useful tool, it may also risk dependency in the day-to-day life of young adults. Such high cell phone dependency may cause various physical, mental and psychological issues that might further lead to several problems in this demographic.

1.2. Epidemiological Data on Dependency of Cell Phone Use (CPU)

The recent estimates of cellular communication prevalence indicated that adult dependency on cell phones in the United States is high compared to other countries. The mobile-cellular subscription rate per capita in the United States was estimated to reach its highest in 2018, making it the third largest subscription rate in the world, only behind the Commonwealth of Independent States (CIS) and Europe (ITU World Telecommunication/ICT indicators database, 2018; The Internet World Stats, 2016). Interestingly, the rate was found to be higher in countries where cell phones were primarily used for communication and social networking (Lopez-Fernandez et al., 2017).

Smartphones are considered to be the modified versions of traditional cellular phones. More precisely, as per the definition, a smartphone is a combination of both cellular (calling and texting) and computer (accessing internet, storing information, installing programs, etc.) capabilities in one small handheld device (Beal, 2008). According to the PEW Research Center (2018), 95% of American adults own a cell phone of some kind, with 77% owning a smartphone. Cell phone ownership of young adults (18 - 29 yrs.) is 100%, with 94% of them owning a smartphone. The data also found that cell phone dependency in American adults has increased over time; the percentage of smartphone users who do not have a broadband connection at home has reached to 20% in 2018, which was 12% in 2016. Recent mobile-cellular subscriptions (e.g., mobile phone or smartphone) indicated that cell-phone ownership in the US has almost saturated (ITU World Telecommunication/ICT indicators database, 2018). This data reflects how cell phone dependency has increased over the years and may continue to escalate in years to come.

One-in-five American adults prefer to have “smartphone-only” internet over traditional home broadband services ("Demographics of Internet and Home Broadband Usage in the United States," 2018). Recently, Perrin and Jiang (2018) from the PEW Research Center, have reported that “39% of 18- to 29-year-olds now go online almost constantly and 49% go online multiple times per day.” Young adults envision cell phones as an integral component of their day-to-day life as they perceive cell phones as a primary tool for accessing the internet. In fact, they perceive cell phones as something that they cannot live without ("Americans’ Views on Mobile Etiquette," 2015). Cell phones have become a fundamental living need in today's world, which explains the high rate of cell phone dependency.

1.3. Data on the Utilization of Cell Phones/CPU

Young adult cell phone operationalization has a wide range, including texting, calling, listening to audio, gaming, emailing, shopping, banking, networking, recording, or using any other app or software. According to the PEW Research Center (2011), 73% of all Americans used their cell phones for texting, with 92% of young adults for texting or taking pictures. Entertainment (70%) and information retrieval (64%) were other top purposes for CPU. Apart from texting, calling, or basic internet browsing, Americans used their cell phones for health information (62%), online banking (57%), and real estate listing (44%) searches ("PEW Research Center," 2015). With vast operationalization capabilities, a cell phone comes with several pros and cons associated with its daily use; the following sections will highlight these advantages and disadvantages.

1.4. Advantages of Cell Phones/CPU

There are several benefits associated with CPU classified in three major categories, i. e., important tools in emergency situations, means to connect, and usefulness for education and wellness (Wade, 2017). More than 40% young adults have found their cell phones helpful in emergency situations and around 51% have found them useful for information retrieval (PEW Research, 2011). This study also found calling, texting, and social networking as key means to connect. Additionally, several cell phone applications enable young adults to use cell phones for educational (i. e., online resources including MOOC, Khan Academy, etc.) and wellness purposes (i. e., Sports Tracker and Health Workout applications) (Wade, 2017). Notable advantages of CPU can be described as portability and transportability, quick and easy communication, accessibility to the internet, safety and rescue for an emergency, tracking capability (locating), and a powerful learning tool (Lombardo, 2015).

1.5. Disadvantages of CPU

Several disadvantages are associated with the use of cell phones. These disadvantages include distractions, heightened levels of danger, increased cheating in exams, sexual abuse, and higher e-waste (Lombardo, 2015). Prevalent data on CPU described disadvantages in terms of risky behavior, abuse, dependency, problematic use, excessive use, and cell phone addiction (De-Sola Gutiérrez, Rodríguez, & Rubio, 2016). The disadvantages were so adverse that the World Health Organization considered CPU to be a public health concern in the year 2015. In other words, there are many disadvantages associated with CPU that vary in number and type, and they may increase with the rapid growth of cell phone operations each day.

The adverse effects on biological materials from direct thermal or indirect non-thermal radio frequency energy produced by cell phones was another matter of concern (Słojewski, 2013). However, studies could only establish these effects on male erectile function (Al–Ali, Patzak, Fischereder, Pummer, & Shamloul, 2013). In addition to physical hazards, CPU has several behavioral risks, and cell phone addiction is one of them. Cell phone addiction (Kwon et al., 2013; Kwon, Kim, Cho, & Yang, 2013) compels young adults to compromise their safety and health and leaves them with difficulty focusing (LaMotte, CNN, 2017). Overall, CPU is found to be associated with numerous disadvantages, which may grow in intensity if not addressed adequately and in a timely manner.

High cell phone dependency may also lead to nomophobia, a disorder coined in 2008 (Mail Online, 2008). Nomophobia, which was termed as a subtype of anxiety in a recent study (Lin, Griffiths, & Pakpour, 2018), was defined by King et al. (2014) as "the modern fear of being unable to communicate through a mobile phone (MP) or the Internet…. Nomophobia is a situational phobia related to agoraphobia and includes the fear of becoming ill and not receiving immediate assistance (p. 28)." Also, Nomophobia was recognized as one of the CPU disorders that young adults encounter (70% within the age range 18-24, 61% within the age range 25-34), with women (70%) being more susceptible than men (61%) (SecurEnvoy, 2012). Excessive CPU has brought the current generation into a dilemma about the use of cell phones. It not only brings positive effects such as instant access to information but also negative effects like dependency and addiction. The important issue requiring immediate attention is how people can best use cell phones without harmful effects.

1.6. Problem Statement: General Overview, Summary and Need for Proposed Research

1.6.1. General Overview: Tech Advancements and Health Problems

Cell phones have evolved in the last two decades as one of the most-used technological communication devices. CPUses include but not limited to texting, calling, gaming, browsing the internet, listening to music, watching videos, and social networking. Texting and calling alone creates several health problems including sleep disorders, depression and anxiety (Murdock, Horissian, & Crichlow-Ball, 2017; Towne et al., 2017; Adams & Kisler, 2013). Texting, calling, and social networking negatively influence academic performance and sleep quality in young adults (Mendoza, Pody, Lee, Kim, & McDonough, 2018; Felisoni & Godoi, 2018; Lepp, Barkley, & Karpinski, 2015; Li, Lepp, & Barkley, 2015; Junco & Cotten, 2012; Eyvazlou, Zarei, Rahimi, & Abazari, 2016). In addition, excessive CPU negatively affects psychological well being (PWB) variables and levels of PWB in this demographic (Park & Lee, 2012; Kumcagiz &

Gunduz, 2016). There is good reason to think high CPU may affect sleep quality, academic performance, and PWB of young adults negatively and could be detrimental to the benefits of the cell phone as a 21st Century communication device.

Despite several advantages and disadvantages, the transformation of cell phones, from a typical communication tool to a multipurpose electronic device, has made these devices popular among users of all ages. Young adults (18 - 29 yrs.) are the largest user demographic (PEW Research, 2018). The affinity of young adults' CPU has increased enormously in previous decades, reaching a plateau in the current decade. Being the largest consumer demographic of cell phones, young adults are the most vulnerable population to be influenced by the disadvantages of CPU. It is therefore imperative to study how CPU habits of young adults are associated with their health and overall well-being.

The next three sections describe the problems associated with the three CPU domains (sleep quality, academic performance, and PWB) then the scope and severity of the problem, the correlational studies, and the need of the proposed research. A brief overview will also be presented on how sleep quality, academic performance, and PWB may interact with each other.

1.6.2. Problems with CPU and Sleep Quality: Need for Proposed Research

Excessive CPU may create sleep disruptions in young adults, as it is linked to low sleep quality, which may further develop into sleep disorders. Most previous studies recruited college students, aged 18-24, as the study sample because, as of fall 2019, eleven million college students in the U.S. were between the age of 18-24 ("College enrollment statistics and student demographic statistics," 2019). The studies have recruited samples from college students and generalized the outcomes to a larger population of young adults. It can be concluded that among young adults, college students are the most representative samples that are ideal for studying CPU habits of the current young adult population. The literature of the present study, therefore, will revolve around studies comprised of samples from college students, aged 18-24, and will generalize outcomes to the larger population of young adults.

Awareness and compulsion to check cell phone notifications are the key factors that affect sleep quality (Murdock et al., 2017; Li et al., 2015). Additional factors such as CPU 'in bed' and CPU 'after lights are out' also negatively influence sleep patterns (Moulin & Chung, 2017; Zarghami, Khalilian, Setareh, & Salehpouret, 2015). These factors collectively lead to cell phone overuse. Excessive CPU is negatively correlated to sleep quality and may be problematic for sleep-related mental health (Eyvazlou et al., 2016; Towne et al., 2017). Nearly 83% of college students use their cell phones within one hour of going to bed (Moulin & Chung, 2017), and around 66% check cell phone notifications before getting out of bed in the morning ("For most smartphone users…," 2017). Also, young adults use their cell phones, on average, 4.4 hours per day (Towne et al., 2017; Eyvazlou et al., 2016) and check notifications 150 times a day ("Which generation is most distracted by their phones?", 2016). Such constant connection of young adults with their cell phones is linked to several sleep disorders, including depression and anxiety (Moulin & Chung, 2017) that may contribute to a sleep-deprived generation (Zarghami et al., 2015; Eyvazlou et al., 2016).

Current studies investigating CPU and sleep quality of young adults have several limitations regarding CPU instruments and study samples (Murdock et al., 2017; Towne et al., 2017; Eyvazlou et al., 2016; Rosen, Carrier, & Cheever, 2013). For example, some studies (i. e., Eyvazlou et al., 2016) have used a CPU scale that was developed in the year 2007; however, it may not suffice for the current young adult population or the advances in cell phone technology. In addition, a study (Li et al., 2015) has shown different components of CPU (i.e., CPU_Night and CPU_Class) to be associated with sleep quality and grade point average (GPA) respectively. The results may not be unilaterally true because CPU from different times of the day or night may affect sleep quality, academic performance, or both.

1.6.3. Problems with CPU and Academic Performance: Need for Proposed Research

High CPU diminishes young adults' academic performance (Felisoni & Godoi, 2018; Mendoza et al., 2018; Lepp et al., 2015). Cell phone activities such as texting, calling, and social media, including Facebook, were found to be distractions for academic activities (Felisoni & Godoi, 2018, Lepp et al., 2015) and correlated with low college grade point average (Junco & Cotten, 2012). Young adults become involved in multi-tasking and task-switching and lose track of their educational goals (Rosen et al., 2013; Junco & Cotten, 2012), resulting in poor performance on exams (Patterson, 2016).

CPU also steals study time, inside and outside the classroom, which negatively influences overall test grades (Bjornsen & Archer, 2015). Use of cell phones during study and/or class distract young adults from academic tasks, which may leave them with low academic performance. Young adult CPU task-switching, particularly during study and/or class, is a major concern and requires researchers' immediate attention.

On the contrary, increased familiarity with cell-phone-mediated-communication (CPMC) was found to have a positive influence on the self-efficacy and behavioral intentions of college students (Han & Yi, 2018). Increased self-efficacy and regulated behavior enabled improvement in CPU perceptions of learning, thereby enhancing academic performance. Such studies have focused on a side of CPU related to self-belief, self-control, ability to modulate behaviors, and ultimately, to academic achievements. However, less ability to use cell phones as learning tools was found to adversely affect academic performance (Han & Yi, 2018). Nevertheless, cell phones can be helpful tools for learning if used wisely.

Although CPU affects collegiate academic performance in various ways, existing studies failed to provide a holistic assessment in terms of cell phone applications, interaction time, and the impact of CPU on the academic performance of a diverse young adult population.

1.6.4. Problems with CPU and PWB: Need for Proposed Research

The psychological well-being, based on the humanistic theories of positive and negative effective functioning, is the key indicator of socio-psychological prosperity in social relationships (Diener et al., 2009a). It is grounded on the principles of developmental and clinical psychology and may be directly linked to the CPU of young adults. A few studies have investigated levels of PWB and associated variables but ended up with conflicting outcomes. For example, PWB variables such as loneliness and depression were negatively associated with CPU (Park & Lee, 2012), whereas, improved levels of PWB were positively associated with lower CPU (Kumcagiz & Gunduz, 2016). However, a direct correlation between CPU and PWB is yet to be investigated.

The socio-psychological prosperity of more extroverted CPUsers is higher than that of less extroverted users because the latter have lower psychological benefits (Park & Lee, 2012). Psychological benefits may have an association with motives, actions, and responses because Park and Lee (2012) have found 'connecting with others' as one of the motives of CPU. This motive helps build social relationships and is negatively associated with PWB variables, such as loneliness and depression. On the contrary, cell phone addiction, termed as smartphone addiction in case of smartphone usage, of young adults was found to be related to low levels of PWB, which jeopardizes their social relationships (Kumcagiz & Gunduz, 2016). CPU was found to be good and bad both for PWB because it builds social relationships but also leads to behavioral issues such as cell phone addiction. Such conflicting outcomes make understanding PWB ambiguous, which itself is a matter of concern for researchers.

It is clear that existing studies (Kumcagiz & Gunduz, 2016; Park & Lee, 2012) have claimed to investigate social implications of CPU and their relationships with PWB but so far, this research has been limited to a superficial analysis of study variables. In addition, these studies have not used the flourishing scale, a specific scale developed to measure PWB (Diener et al., 2009b) and did not investigate a direct relationship between CPU and PWB. As a result, problems with CPU and PWB are an entirely new area of research.

1.7. Purpose of the Study

As indicated earlier, there is a need to understand CPU habits of young adults using samples from a current collegiate population. The presented study is therefore proposed to investigate the CPU habits of undergraduate students from a large university in the United States in three domains: sleep quality, academic performance, and psychological well-being. More specifically, this study will examine the relationship between CPU and sleep quality. Additionally, the study examines the relationship between CPU and academic performance of this focused group. Finally, it examines the relationship between CPU and PWB.

1.8. Research Questions

The proposed study is guided, broadly, by the following research questions:

RQ1: How does the CPU of undergraduate students correlate to their sleep latency and sleep difficulty?

RQ2: How does the CPU of undergraduate students for switching away from class/lecture, lab, and or study sessions and for self-regulated learning behaviors correlate to their academic performance?

RQ3: How does the cell phone social media use of undergraduate students correlate to their psychological well-being?

1.9. Theoretical Framework

In the present study, the hypotheses from the domains of sleep quality, academic performance, and PWB are supported by various learning and developmental theories nested under the broader umbrella of cognitivism. The hierarchical model of the theoretical framework in this study is based on the perspectives on learning provided by Ormrod (2016) and is comprised of four overarching theories: information processing, cognitive neurology, social cognition, and contextual (including sociocultural) processes. The theoretical framework for the cell phone use study is shown in Fig. 1.1.

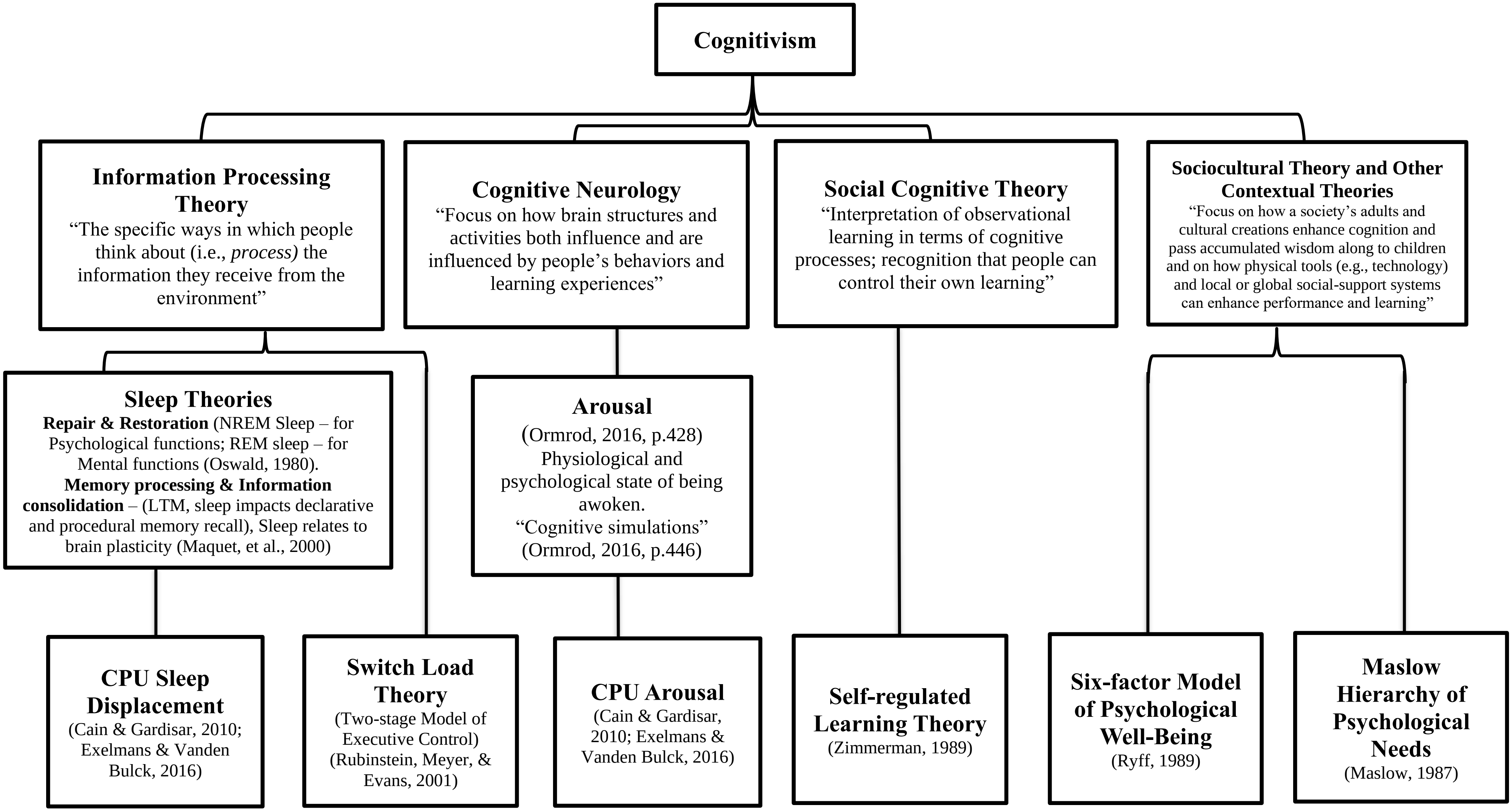

Figure 1. Theoretical Framework of Cell Phone Use Study

Drawing on Ormrod's perspective on learning, the present study laid its foundation on six learning theories grouped under the aforementioned four overarching theories. The Switch Load Theory, Self-regulated Learning Theory, Six-factor Model of Psychological Well-Being, and the Maslow's Hierarchy of Psychological Needs are linked directly to the overarching theories; however, the CPU Sleep Displacement and CPU Arousal are best described as being routed through more specific sleep and arousal theories. More specifically, Sleep Displacement and Switch Load Theory were kept under the first overarching theory, i.e., Information Processing Theory (Ormrod, 2016); however, the Sleep Displacement mechanism was seen through the lens of Sleep Theories based on repair and restoration (Oswald, 1980), and memory processing and information consolidation (Maquet, et al., 2000). The CPU Arousal mechanism was placed under the second overarching theory, i.e., Cognitive Neurology (Ormrod, 2016), however, was seen through the lens of Arousal, which was described as cognitive simulation by Ormrod.

The Self-regulated Learning Theory (Zimmerman, 1989) was related to the third overarching theory, i.e., Social Cognitive Theory. The Social Cognitive Theory of self-regulation, based on the model of triadic reciprocal determinism, emphasized the key functions that influence human behavior. According to Bandura (1991, p. 248), "the major self-regulative mechanism operates through three principal subfunctions. These include self-monitoring of one's behavior, its determinants, and its effects; judgment of one's behavior in relation to personal standards and environmental circumstances; and affective self-reaction.”

The Six-factor Model of Psychological Well-Being (Ryff, 1989) and Maslow's Hierarchy of Psychological Needs (Maslow, 1987) were placed under the fourth overarching theory, i.e., Sociocultural Theory and other Contextual Theories (Ormrod, 2016). These theories suggest that social factors are vital for cognitive development (Vygotsky, 1978). The sociocultural aspect of learning develops the cognitive outlook of well-being, such as gratitude, self-esteem, optimism, locus of control/autonomy, competence, connectedness, attributional style, etc. (Margolis & Lyubomirsky, 2018). The components of the cognitive outlook of well-being closely relate to the factors of psychological well-being and psychological needs.

The literature review from chapter two of the dissertation provides further details on the six learning theories and their connection with specific research questions and research hypothesis.

1.10. The Significance of the Study: New Knowledge to the Existing Body of Literature

1.10.1. Significance Pertaining to CPU measures

Previous studies from the domains of sleep quality, academic performance, and PWB have called for a need to implement comprehensive measures capturing more CPU activities/operations. For example, the studies from the domains of sleep quality and academic performance focused on CPU texting and calling (Mendoza, et al., 2018;

Blasiman, Larabee, & Fabry, 2018; Exelmans & Van den Bulk, 2016; Zarghami et al., 2015; Lawson & Henderson, 2015). The studies from the PWB domain also assessed CPU texting and calling in addition to measuring other CPU activities/operations, such as emailing and social networking (Hoffner & Lee, 2015). Additionally, the studies from the PWB domain assessed the use of cell phones in terms of smartphone addiction using the Smartphone Addiction Scale (Kumcagiz & Gunduz, 2016; Kwon et al., 2013). Some other studies have examined CPU in terms of total time spent on cell phones (Mendoza, et al., 2018; Pettijohn et al., 2015), nighttime cell phone notifications (Murdock et al., 2017, 2019; Dowdell et al., 2018), and cell phone screen time (Xu et al., 2019; Melton et al., 2014). The presented study expands upon the work cited by using measures comprised of CPU activities/operations, which may potentially correlate to cognitive, emotional, or psychological disturbances.

1.10.2. Significance Pertaining to Study Samples

The study data of existing literature from all three domains consists of samples restricted to the scope and subject major. For example, studies from the sleep quality domain were comprised of samples mostly from students majoring in medical sciences (Eyvazlou et al., 2016, n=450; Zarghami et al., 2015, n=358) and liberal arts majors (Murdock, et al., 2017, n=83; Murdock, et al., 2019, n=425). Some notable studies from this domain did not provide information on the participants' majors (*Dowdell & Clayton, 2018, n=372;* Blasiman et al., 2018, n=109; Moulin & Chung, 2017, n=89). Studies from the academic performance domain had samples from liberal arts majors (Mendoza et al., 2018, n=160), information technology majors (Fernandez, 2018, n=179), and business majors (Felisoni & Godoi, 2018, n=43). Samples within this domain encompassed various majors, including social sciences, medical/health sciences, education, business, and the humanities (Pettijohn et al., 2015, n=235; Lepp et al., 2015, n=536).

Studies from the PWB domain were comprised of samples from liberal arts majors (Murdock, et al., 2015, n=142) and education majors (Kumcagiz & Gunduz, 2016, n=408; Hoffner & Lee, 2015, n=287). A few studies in the same domain did not provide any information on participants' majors at all (Chan, 2013, n=514; Park & Lee, 2012, n=279). The presented study uses a diverse sample of college students from 14 majors including, the College of Engineering, the College of Agriculture and Life Sciences, the College of Liberal Arts, the College of Science, the College of Education and Human Development, Mays Business School, and the College of Veterinary Medicine and Biomedical Sciences. This study contributes to these many studies by utilizing a more varied student sample.

1.10.3. Significance Pertaining to the Domain of CPU and Sleep Quality

1.10.3.1. Investigating CPU, CPU Before Bed, and CPU Arousal

Previous studies examining the correlation between CPU and sleep quality have not assessed CPU as a separate independent variable. For example, authors Towne et al. (2017), Moulin and Chung (2017), and Adams and Kisler (2013) have assessed the use of technology as a whole, but CPU was just one of many components. In another study

(Melton, Bigham, Bland, Bird, & Fairman, 2014), CPU was assessed through a single sub-question asking for the total number of hours college students spend on phone applications, which was part of a larger construct measuring health technology use. Notably, Melton et al. did not include any item in the general technology use construct assessing the use of cell phones. The presented study investigates CPU as an independent variable, and examines the components of CPU in terms of CPU before bed and CPU arousal.

1.10.3.2. Examining the Correlation between CPU and Sleep Components

Previous studies from this domain have not examined the correlation of sleep components, sleep latency and sleep difficulty, with CPU factors, CPU before bed and CPU arousal. For example, studies from authors Murdock, Horissian, and Crichlow-Ball (2017) and from several others including, Chen and Li (2017), Eyvazlou et al. (2016), Lepp et al. (2015), and Demirci et al. (2015) have assessed the correlation of CPU with the overall sleep quality of young adults. Also, previous studies have provided a subjective assessment of sleep quality. For example, studies from authors Tao et al. (2017), Adams and Kisler (2013), and Harada et al. (2006) have assessed the subjective sleep quality of young adults. In addition, previous studies have used sleep diaries for assessing the duration of sleep (Murdock, et al., 2017). Moreover, some studies have used just one item for assessing the hours of sleep during 24 hours (Towne et al. 2017). The presented study investigates the correlation of specific sleep components, sleep latency and sleep difficulty, with the CPU factors, CPU before bed and CPU arousal, along with examining the correlation of CPU with overall sleep quality from a period of 30 days by using a validated scale, i.e., Pittsburgh Sleep Quality Index (PSQI), of 19 items.

1.10.3.3. Investigating CPU Arousal and its correlation with Sleep difficulty and Sleep Quality

Nighttime CPU, especially just before and after going to bed, may increase mental (cognitive), emotional, or psychological arousal (Cain & Gradisar, 2010) in young adults, which may potentially create sleep disturbance (sleep difficulty) in this demographic. Previous studies have investigated a correlation between violent and sexual media content, and arousal (Anderson et al., 2010; Van der Molen & Bushman, 2008). However, a correlation between arousal due to media content and sleep quality was not yet investigated. In other words, it is yet unknown how CPU arousal correlates with sleep disturbance (sleep difficulty), and with overall sleep quality of young adults. Further, previous studies have investigated sexting, “using technology to create, send, and receive sexually explicit photos, videos, and/or text-only messages” (Fleschler Peskin et al., 2013) among high school students, but have not examined how sexting may affect sleep quality.

The presented study investigates arousal due to the use of cell phones to engage in emotionally charged text messages and images, in explicit content pertaining to sexuality (pornography, tinder, dating sites, etc.), and in explicit content pertaining to violence (video games, movies, etc.) just before or after going to bed at night. The study also examines the relationship that CPU arousal may have with sleep difficulty and with overall sleep quality of young adults. Examining CPU arousal for the young adult demographic differentiates the presented study from previous studies, thus adds new knowledge to the existing body of literature.

1.10.3.4. Theoretical Support to the Established Correlations between CPU and Sleep Components

Previous studies (Murdock et al., 2019, 2017; Xu, Adams, Cohen, Earp, & Greaney, 2019; Dowdell & Clayton, 2018; Towne et al., 2017; Tao et al., 2017; Chen & Li, 2017) have not explored the correlation of sleep components, sleep latency, and sleep difficulty (sleep disturbance), with the use of cell phones from specific times of the day and night, and for specific purposes. In addition, these studies have not provided theoretical support to the established correlations of examined variables. This study provides a clear justification of how and why nighttime CPU may affect sleep latency, sleep difficulty, and overall sleep quality of young adults as the sleep hypotheses are supported by sleep disruption theories. For example, the sleep latency hypothesis has been supported by sleep displacement theory, and sleep difficulty hypothesis has been supported by the arousal theory. Outcomes of the sleep latency hypothesis will explain how the use of cell phones for unstructured leisure activities before sleep may affect sleep latency. The outcomes of the sleep difficulty hypothesis will explain how accessing explicit or emotionally charged media content before sleep may affect sleep difficulty. Examining the relationship of the use of cell phones from different times and for different purposes, with respective sleep components and overall sleep quality, differentiates this study from existing literature. Providing theoretical support to the established correlations between the study variables also makes this study different from previous studies.

1.10.4. Significance Pertaining to the Domain of CPU and Academic Performance

1.10.4.1. Investigating Cell Phone Media-multitasking

Cell phones are ubiquitous handheld electronic devices that young adults use widely and wildly, even in the classroom. The role of cell phones has been underestimated in previous studies while assessing the impact of media multitasking on the academic performance of the young adult demographic. For example, Patterson (2016) investigated the impact of digital media multitasking on exam performance, however, did not provide any information on the digital devices used for multitasking. Another example can be drawn from a study examining the impact of various distractions on learning during an online lecture (Blasiman, Larabee, and Fabry, 2018). Blasiman et al. have considered texting as the only cell phone activity/operation for measuring distraction due to the use of cell phones while listening to the lecture. One more example comes from a recent study (Redner, Lang, & Brandt, 2019) that investigated the impact of electronic usage as a whole on academic performance. Assessing the use of all electronic devices may not provide a clear picture on classroom cell phone media multitasking. The presented study investigates cell phone media multitasking during a class/lecture, lab, and/or study session, which advances the existing literature on digital media multitasking.

1.10.4.2. Investigating CPU Switching Frequency during Academic Tasks

Previous studies have measured the total time college students spend on cell phones during class and/or study sessions (Mendoza et al., 2018; Pettijohn et al., 2015; Lawson & Henderson, 2015; Gingerich & Lineweaver, 2014; Froese et al., 2012;). Also, these studies have focused on texting and calling, which may not be the complete representation of all cell phone activities/operations that influenced academic performance. Irrespective of measuring the total time spent on cell phones, the presented study investigates the number of times college students switch to their cell phones during class, lab, and/or study sessions. In addition, this study examines switching frequency for potential cell phone activities/operations influencing academic performance, i.e., texting, calling, emailing, shopping, banking, surfing the internet, and gaming, which differentiates the presented study from the existing literature on this specific domain.

1.10.4.3. Examining CPU during Class/Lecture, Lab, and/or Study Session

Previous studies investigating CPU and academic performance provide the correlation between per-day-CPU and academic performance (Felisoni & Godoi, 2018; Lepp et al., 2015). Some studies have investigated students' perceptions and attitudes towards the use of cell phones in the classroom. For example, a study from authors Berry and Westfall (2015) examined college students' daily CPU, their perceptions and attitudes towards CPU, and classroom policies. Another study from Fernandez (2018) assessed students' views on classroom CPU, and one study from authors Tossell et al. (2015) presented student perceptions of CPU for educational purposes over one year. Such outcomes may not provide accurate information on how exactly the use of cell phones during class and/or study sessions affected academic performance. This study examines college students CPU in a 60-minute block of time related to class/lecture, lab, and/or study session, which will help researchers understand how the use of cell phones affects the academic performance of college students.

1.10.4.4. Examining CPU for Self-Regulated Learning Behaviors

The potential positive aspects, such as the use of cell phones for self-regulated learning behaviors, were ignored in previous studies examining CPU and academic performance. Most of the studies (Mendoza et al., 2018, Felisoni and Godoi, 2018, Pettijohn et al., 2015, Lawson and Henderson, 2015, and Lepp et al., 2015) have focused only on time spent on classroom cell phone activities and on how such activities influenced academic grades. In a way, these studies over-represented the time spent on classroom CPU and the negative correlation between CPU and academic performance in existing literature. Some other studies, for example Ya'u and Idris (2015) and Han and Yi (2018), have investigated students' behavioral intentions towards the use of cell phones in the classroom, but have overlooked examining the use of cell phones for self-regulated learning behaviors. This study, therefore, irrespective of just examining the correlation between CPU and academic performance, identifies the pros and cons of the use of cell phones for academic purposes. The study both investigates the use of cell phones during a class/lecture, lab, and/or study session, and it examines the use of cell phones for self-regulated learning behaviors, which makes this study different from the existing literature.

1.10.4.5. Theoretical Support to the Established Correlation between CPU and Academic Performance

Authors from previous studies have used different approaches to establish a connection between classroom CPU and academic performance. For example, some authors, including Mendoza et al. (2018), Felisoni and Godoi (2018), Lawson and Henderson (2015), Gingerich and Lineweaver (2014), and Rosen et al., (2011) have used experimental methods. Authors, including, Pettijohn et al. (2015), Lepp et al. (2015), Tossell et al. (2015), and Braguglia (2008) have used quantitative survey methods. Authors, including Bjornsen and Archer (2015), and Froese et al. (2012) have used both of these methods. However, these studies have not provided a theoretical justification of how and why classroom CPU influences academic performance, and how and why the use of cell phones for self-regulated learning behaviors can improve academic performance. The present study attempts to provide a clear justification of how and why CPU affects academic performance as both the hypotheses from academic performance domain are based on existing theories. The CPU classroom hypothesis is based on switch-load theory and the CPU self-regulated learning hypothesis is based on the Zimmerman theory of self-regulated learning. The CPU classroom hypothesis investigates how the frequency of switching away from class/lecture, lab, and/or study sessions using a cell phone may affect academic performance. The CPU self-regulated learning hypothesis investigates how the use of cell phones for self-regulated behaviors may help improve academic performance. Such specific analysis of young adult CPU during/for academic activities makes this study stand out and will add new information to the existing body of literature.

1.10.5. Significance Pertaining to the Domain of CPU and PWB

1.10.5.1. Exploring the CPU and PWB of Young Adults

The CPU of young adults was examined with health variables along with the subjective well-being (SWB) in previous studies; however, CPU and PWB was left unexplored. Several health variables were found to be influenced by the use of cell phones, i.e., numbness or burning sensation on ears (Al-Khamees, 2007), headache, laziness and tiredness (Zarghami et al., 2015), daytime dysfunctioning (Zarghami et al., 2015), mental overload (Thomee et al., 2010), and stress, anxiety and depression (Thomee et al., 2007; Adams & Kisler, 2013; Lepp et al., 2014; Demirci et al., 2015; Tao et al., 2017). The SWB of young adults was assessed in terms of satisfaction with life (Volkmer & Lermer, 2019; Li et al., 2015; Lepp et al., 2014), emotional and relational well-being (McDaniel & Drouin, 2019), and overall well-being (Hoffner & Lee, 2015; Volkmer & Lermer, 2019), and was found to be correlated with CPU. The present study explores CPU and PWB of the young adult demographic, which will be new information in this area of research.

1.10.5.2. Investigating the Direct Relationship between the CPU and PWB of Young Adults

Some previous studies have claimed to investigate CPU and PWB; however, they either astray from assessing a direct correlation between CPU and PWB or end up with conflicting outcomes. For example, Chan (2013) investigated the use of cell phones in terms of four CPU dimensions (voice communication, online communication, information seeking activities, and time-pass activities), and focused only on the emotional aspect of well-being. Chen and Li (2017) examined how communicative uses of cell phones, including friending self-disclosure, may help predict PWB through bonding and bridging social capital. Further, Murdock, Gorman, and Robbins (2015) investigated how co-rumination via cell phones moderate the association of perceived interpersonal stress and PWB. Examples of conflicting outcomes arise from the following two studies. The first study (Park & Lee, 2012) shows a negative correlation between CPU and PWB variables, such as loneliness and depression, whereas the second study (Kumcagiz & Gunduz, 2016) shows a positive correlation between low CPU and the improved levels of PWB. Similarly, in the first study, the socio-psychological prosperity of more extroverted cell phone users was found to be higher than that of less extroverted cell phone users, and in the second study, high CPU was found to be related to low levels of PWB. The present study will help resolve existing conflicts about the correlation between CPU and PWB by investigating a direct relationship between CPU and PWB.

1.10.5.3. Theoretical Support to the Established Correlation between CPU and PWB

One reason why previous studies from this domain (Chen & Li, 2017; Kumcagiz & Gunduz, 2016; Murdock, et al., 2015; Chan, 2013; Park & Lee, 2012) lacked theoretical support perhaps because a direct correlation between CPU and PWB was not investigated in these studies. This study will examine two CPU social media hypotheses: CPU social media feelings and CPU social media responses, and both the hypotheses will be supported by the existing developmental theories. The CPU social media feeling hypothesis will be supported by the humanistic theories of positive functioning, and the CPU social media response hypothesis will be supported by two theories: Maslow hierarchy of needs and self-determinant theory. The hypotheses from this specific domain were expected to assess well-being components (the feeling of engagement and interest, pleasure, meaning and purpose, and optimism) and psychological need components (affiliation, social interaction, friendship, giving and receiving, and the feeling of accomplishments) of young adults. These hypotheses aimed to examine the correlation between CPU and PWB of the young adult demographic, which will be new knowledge for the literature from developmental science research.

1.11. Potential Practical Implications and Application to the Real World

The outcomes of the presented study will have several practical implications for CPUsers from young adult and other user demographics on the risk of excessive/constant CPU. In addition, results will guide future researchers for examining not only the negative aspect of CPU but also the positive side of the use of cell phones. The study will also serve as a guiding document for health professionals and cell phone manufacturers. Following sections describe the implications from the three specific domains: sleep quality, academic performance, and PWB.

1.11.1. Implications from the Domain of CPU and Sleep Quality

The established correlation between nighttime CPU and sleep quality will shed light on the harmful effects of bedtime CPU, and therefore, will guide CPUsers to limit their nighttime cell phone screen time. More specifically, the known correlation between CPU before bed and sleep latency will help educate excessive CPUsers to regulate before-bed CPU habits. Knowing the impact of CPU, especially for unstructured leisure activities, and for accessing emotionally charged media content before bed, on sleep difficulty (sleep disturbance), will create awareness about the usage of cell phones from a specific time, particularly during evening/night, and for a specific purpose. Such awareness will help regulate CPU nighttime behaviors, for example, putting cell phones away before sleep hours and avoiding accessing emotionally charged media content before sleep. Such interventions will also help prevent the current generation from sleep deprivation. Additionally, the outcomes of this domain of the study will have recurring implications for clinical and non-clinical future studies, for CPUsers, health professionals, and for cell phones manufacturers.

1.11.2. Implications from the Domain of CPU and Academic Performance

The outcomes from this domain of the study will provide clear guidelines on the feasibility of CPU during class/lecture, lab, and/or study session, and for other study-related tasks, which will have direct implications in the field of education. The correlation between CPU switch, i.e., classroom CPU, and academic performance will help make a clear case of why cell phones should or should not be used for or during academic pursuits. The statistical data on CPU classroom task-switching will help develop preventive measures on classroom multitasking. The data on cell phone self-regulated behaviors (metacognitive, motivational, and behavioral) will help educate young adults with self-control strategies, which will help improve their self-efficacy. This data will also potentially help teachers to integrate cell phones into classrooms for various teaching-learning purposes including: adhering to study schedules, setting goals, monitoring student progress, and for reinforcing classroom instruction. With negative and positive attributes established, CPU supported self-regulation interventions may be generated to not let CPU take control of our learning, which will be the most significant practical implication of the outcomes from this study.

1.11.3. Implications from the Domain of CPU and PWB

Social media is the biggest virtual platform where young adults portray their lives to the public, and cell phones are the most accessible devices suitable for that purpose. The presented study provides comprehensive data on CPU social media feeling and CPU social media responses of the young adult demographic. Specifically, the data on CPU social media feelings will inform us about how a cell phone makes participants feel from a social media standpoint (Instagram, Twitter, Facebook, Snapchat, LinkedIn, etc.) along different dimensions: engagement and connectedness, interest, pleasure and sense of enjoyment, meaningfulness, purposefulness, optimism, belongingness and acceptance, and competence and feeling accomplished. The data on CPU social media responses will tell us how young adults perceive a response to their own posts and their own responses to others' posts on cell phone social media. CPU social media response data will also educate us about the feelings of connectedness, being liked by others, reward, and contributing to the well-being of others based on responses with social media apps (Instagram, Twitter, Facebook, Snapchat, LinkedIn, etc.). The established correlation between CPU and PWB will have direct practical implications, as it will inform us on how cell phone social media shall be used as a potential tool for fulfilling psychological needs.

2. LITERATURE REVIEW

2.1. Introduction

The capability of cell phones, which has increased at a rapid rate, attracts users of all ages; however, affinity toward the CPU is uniquely overwhelming in young adults (PEW Research, 2011; PEW Research, 2018). Key factors that motivate this demographic to use cell phones include: caring for others, following trends, communication, information, accessibility, and passing the time (Park & Lee, 2012). These factors collectively aggregated in checking cell phones around 150 times a day ("Which generation…," 2016). In a broad sense, such constant connection has greatly increased cell phone dependency of young adults ("U.S. smartphone users statistics in 2017: a 'Round-the-Clock' connection," 2017). High dependency on cell phones occupies a significant amount of time meant for other important activities including sleep, study, and socializing. While CPU has its advantages, overuse can override these benefits.

Young adults use their cell phones for various purposes, which may compel them to be frequent CPUsers. The high frequency of CPU, including texting, calling, social media, and checking cell phone notifications just before and after sleep, may affect sleep quality in many ways. CPU may also impact academic performance if the study time is consumed predominantly by the use of cell phones inside and outside the classroom. In addition, CPU may influence PWB, which further affects societal and emotional outcomes of well-being. Overall, excessive CPU, directly or indirectly, costs time, which forces young adults to compromise with their sleep, study and social interaction. Although motivational drives to CPU for learning are “control (over learners’ goals), ownership, learning-in-context, continuity between contexts, fun, and communication” (Jones & Issroff, 2007), a rapid increase in the capabilities of cell phones may be a key factor that contributes to CPU habits. Nevertheless, the affinity towards cell phones may depend on, and change with, time and place. The CPU from different times of the day and night adds up to the total CPU that may relate to young adults’ sleep quality, academic performance, and PWB differently.

Before investigating how CPU affects the sleep quality, academic performance, and PWB of young adults, it is necessary to understand how previous researchers have perceived these variables. It is also essential to know the current status of research concerning the impact of CPU on sleep quality, academic performance, and PWB as well as theoretical principles that form a basis for this thesis. The literature review, therefore, will focus on five areas of the research concerning CPU. The first section will define study variables, i. e., CPU, sleep quality, academic performance, and PWB. The second section will highlight the impact of CPU on sleep quality. The third section will focus on the impact of CPU on academic performance. The fourth section will outline the current status of research concerning CPU and PWB, while the last section will present multiple research hypotheses based on theoretical principles concerning the relationship between CPU and sleep quality, academic performance, and PWB.

2.2. Definition of Study Variables

2.2.1. Cell Phone Use (CPU)

CPU was defined by PEW Research (2011) in terms of various uses of a cell phone, including texting, calling, accessing the internet and social networking sites, playing games, playing music, watching videos, and participating in video calls or chats. This study will use a modified version of this definition, defining CPU as calling, texting, podcasting, gaming, browsing the Internet (shopping, surfing, scrolling, etc.), listening to music, watching videos (Netflix, Hulu etc.), using social media (Instagram, Twitter, Snapchat, Facebook, LinkedIn, etc), sending and receiving emails, and using other app- or software not listed above. CPU for the purpose of this study includes time spent on cell phones (i. e., mobile phones) and smartphones.

2.2.2. Sleep Quality

Sleep quality was described in terms of the Pittsburgh Sleep Quality Index (PSQI), which is comprised of seven components including sleep latency, sleep disturbances (sleep difficulty) and daytime dysfunction (Buysse, Reynolds, Monk, Berman, & Kupfer, 1989). Sleep latency was defined as the amount of time it takes for one to fall asleep, as well as how often (a day, a week or a month) one cannot get to sleep. Sleep disturbances (sleep difficulty) were described as the frequency of waking up at night, or in the early morning, for various reasons. Finally, daytime dysfunction was assessed by how often one had trouble staying awake while driving, eating meals, or engaging in social activities, and struggled to keep up enough enthusiasm for daily activities (Buysse et al., 1989). For the purpose of present study, sleep quality will be defined in terms of seven crucial components of sleep as these were defined by (Buysse et al., 1989). However, current study will focus more on sleep latency and sleep disturbances (sleep difficulty).

2.2.3. Academic Performance (GPA)

Academic performance was defined by scores on content-based quizzes or tests (Elder, 2013; Froese et al., 2012; Gingerich & Lineweaver, 2014; Lawson & Henderson, 2015), however, was used differently. For example, Katz and Lambert (2016) defined academic performance as the test scores over the course of a semester. Authors Bjornsen and Archer (2015) furthered this study but looked at test scores across multiple semesters to define academic performance. Harman and Sato (2011) and Tossell, Kortum, Shepard, Rahmati, and Zhong (2015) used a grade point average, and McDonald (2013) used final course grades to assess academic performance. For the present study, the academic performance will be defined as the self-reported grade point average (GPA) of the undergraduate students, as it is defined by Lepp et al. (2014), Harman and Sato (2011), and Tossell et al. (2015).

2.2.4. Psychological Well-being (PWB)

The PWB of a person is based on the humanistic theories of positive and negative effective functioning and is distinctly different from that of the subjective well-being (Diener et al., 2009a; Ryff, 1989). A new well-being measure consists of psychological and emotional aspects of well-being and uses the flourishing scale and the scale of positive and negative experiences to assess these components (Diener et al., 2009a, Diener et al., 2009b). The following study will investigate PWB because PWB has been found to be an indicator of the socio-psychological prosperity of social relationships. In addition, PWB represents optimal human functioning (Diener et al., 2009a). For the purpose of present study, PWB will be defined exactly how it was defined in previous studies (Ryff, 1989; Diener et al., 2009a), which is:

> The aspects of psychological well-being we assess in the Psychological Well-Being (PWB) Scale, and names of some of those who have been advocates for the desirability of these states are: Meaning and purpose, Supportive and rewarding relationships, Engaged and interested, Contribute to the well-being of others, Competency, Self-acceptance, Optimism, and Being respected.

2.3. CPU and Sleep Quality

2.3.1. Brief Overview

Investigating the impact of CPU on the sleep quality of college students would be worthwhile because the CPU habits of young adults may be regularly changing with the constant addition of new and updated cell phone operations (applications). More cell phone operations require more time and thus may leave young adults with less or limited time for healthy sleep. Unhealthy sleep may create several mental, physical and emotional disorders. It is, therefore, necessary to understand how the CPU of young adults influence their sleep quality. The literature review guided by this particular question is comprised of four key sections: relevant prevalence and scope data on CPU and sleep quality, the relationship between CPU and sleep quality, underlying theories, and the summary of the literature review.

2.3.2. Relevant Prevalence and Scope Data Concerning CPU and Sleep Quality

The times during the day when young adults' CPU was the highest were the hours right before bed and right after waking up. Three-quarters of Americans keep their cell phones turned on round-the-clock ("U.S. smartphone users…," 2017). The seamless and restriction-free access to cell phones, in terms of time and place, in the day-to-day life, enables young adults to interact with their cell phones at all times. Moreover, frequent use of cell phones, especially when used for a long time in one sitting, makes young adults evening-oriented, which further results in psychiatry issues that may be caused due to de-synchronization of circadian oscillations (Harada, Morikuni, Yoshi, Yamashita, & Takeuchi, 2002).

It was reconfirmed by several studies (Tao et al., 2017; Murdock et al., 2017) that texting and calling are the most used features of cell phones, which contributes to the majority of sleep disorders concerning CPU. Such CPU-led sleep disorders further created a sleep-deprived generation, as sleep latency and daytime dysfunctioning exacerbate symptoms of insomnia in young adults (Zarghami et al., 2015). It is clear that high CPU is linked with low sleep quality. Overusing cell phones for different activities, including browsing the internet and social media, may worsen sleep quality.

Since the beginning of the current decade, sleep disorders, "a group of conditions in which the normal sleep patterns or sleep behaviors are disturbed ("Sleep disorders," 2018)," due to high CPU have become so prevalent that CPU-led sleep quality became a matter of concern for contemporary researchers. Adams and Kisler (2013) have found that 47% of the college students in the sample woke-up at night just to respond to their text messages and 40% to answer phone calls. From this data, 29% of the college students woke-up once or twice, and 27.5%
woke-up thrice or more to respond to their calls or text messages. Adams and Kisler (2013) further concluded that CPU led sleep quality mediates between CPU and sleep-related variables, such as depression and anxiety.

Previous researchers show that college students in particular are susceptible to CPU-led sleep deficiencies and young adults are the largest demographic influenced by CPU. Constantly increasing operations and open access to social media make cell phones more engaging. Such engagements force young adults to spend most of their time with cell phones and leave them as excessive CPUsers. Excessive CPU may contribute to poor sleep quality and associated disorders in this demographic, which end-up creating generations of sleep-deficient individuals.

2.3.3. Existing Relationships between CPU and Sleep Quality

The literature review revealed that empirical studies pertaining to the impact of CPU on sleep quality, and associated disorders, first appeared in the early 21st century. The impact of high CPU on sleep components, i. e., sleep disturbance and sleep latency was reported by Harada et al. (2002) who also found that frequent CPU, especially for more than 20 minutes per one usage, enables young adults to be more “evening-oriented” (2002). Evening-orientedness was described as having less emotional stability and poor stress handling capability due to lack of sleep, which makes a person vulnerable to psychological issues. Similar consequences were reported by authors Harada, Tanoue, & Takeuchi (2006), who stated that “the night usage of convenience stores, mobile phones and watching midnight TV makes senior students shift to being evening-type people.” High CPU has been detrimental to emotional and psychological stability since the inception of the digital age, however, symptoms of disorders were especially intense in night users of electronic devices.

The damaging effects of CPU on sleep quality has increased in the last two decades. These effects have become even more intense in the latter part of the previous decade and have compelled researchers to shift their focus from studying ‘the impact of information communication technology (ICT) as a whole’ to studying ‘the impact of CPU alone’ (Thomee, Eklöf, Gustafsson, Nilsson, & Hagberg, 2007; Thomee et al., 2010). As per Thomee et al. (2010), young adults perceive cell phones as devices that compel them to be available round the clock, which further causes sleep disturbances. However, several other factors such as cell-phone-notifications (sound or vibration), electromagnetic radiation (blinking light), thought-provoking (disturbing) content, and long phone calls (or texts) just before bedtime also influenced participants’ sleep quality. An additional Thomee, Härenstam, & Hagberg (2011) study found that CPU was negatively correlated with the sleep disturbance of young adults; however, the study has confirmed this relationship through a number of cross-sectional correlations between CPU, sleep disturbance, stress, and depression.

High smartphone usage and sleep quality were also found to be negatively correlated with each other in an additional sample of college students (Demirci et al., 2015). In this study, the Smartphone Addiction Scale Scores of female students were found to be significantly higher than that of male students. Further, high CPU was found to be positively correlated with sleep disturbance and daytime dysfunction, and negatively with subjective sleep quality in the overall sample of the study. Authors Zarghami et al. (2015) discovered that college students use their cell phones after the lights were out, which caused sleep latency and daytime dysfunction. In summary, excessive CPU not only affected sleep quality but also the associated factors such as daytime dysfunction.

Problematic mobile phone use (PMPU), "an inability to regulate one's use of the mobile phone, which involves negative consequences in daily life (Billieux, 2012, p. 299)," was found to be correlated with mental health symptoms and poor sleep quality in 28.2% of a large sample of college students (Tao et al., 2017). Calling and texting after lights out were the key contributors to PMPU that substantially created sleep disturbances (Munezawa et al., 2011). PMPU sleep disturbances include short sleep duration, excessive daytime sleepiness, subjective sleep quality, and insomnia symptoms. Tao et al., (2017) have also found that the risks of mental disorders in college students with PMPU were more likely to develop and were significantly associated with CPU-led poor sleep quality. It can be concluded from the above studies that issues concerning high CPU and PMPU are somewhat similar and leads to sleep disorders in young adults.

The short message service (SMS or text messaging) of cell phones is the highest used function for communication purposes in America (Smith, 2015). Text messaging was found to be significantly associated with the foremost components of sleep quality: sleep difficulty (sleep disturbances) and sleep latency (Murdock et al., 2017; Adams & Kisler, 2013; Thomée et al., 2007; Al-Khamees, 2007). Increased number of daily texts, due to recurrent cell phone notification cycles (receiving notifications, checking them and texting back), was found to be associated with sleep disruptions, and other sleep disorders, in young adults, leading to poor subjective sleep quality (Murdock et al., 2017). Further, nighttime cell phone notification cycles alone caused higher global sleep problems and sleep disruptions.

2.3.4. Underlying Theories

High frequency of CPU may disrupt sleep through three possible mechanisms (Cain & Gradisar, 2010): exposure to bright light (melatonin hypothesis; hormonal secretion), sleep displacement (place hypothesis; CPU in bed), and media content (arousal hypothesis) (Tosini, Ferguson, & Tsubota, 2016; Clayton, Leshner, & Almond, 2015; Exelmans & Van den Bulck, 2016). Most researchers, however, are concerned with the exposure to the bright light emitted from cell phones.

The bright light, particularly in the shorter wavelength range (blue light: 446 – 483 nm), impacts both human physiology, such as hormonal secretion (Brainard et al., 2001; Cajochen et al., 2005; Chellappa et al., 2013), and human behavior, such as clock gene expression or circadian rhythms (Cajochen et al., 2006). Melatonin suppression is a phenomenon in which the short-wavelength blue light emitted from self-luminous electronic devices such as cell phones influences hormonal secretion and circadian rhythm, thereby leading to irregular sleep patterns (Tosini et al., 2016; Wood, Rea, Plitnick, & Figueiro, 2013). Briefly, CPU at night affects hormonal secretion perturbing the circadian clock cycle and ultimately impacts sleep quality (Blask, Sauer, Dauchy, Holowachuk, & Ruhoff, 1999).

Sleep displacement theory is based on the concept in which the use of electronic media for unstructured leisure, with no time limit, displaces several activities including sleep (Kubey, 1986; Van den Bulk, 2004). Displacement of sleep happens when the brain believes it is still working because one continues to use a cell phone while in bed, creating an association in the brain between the location of CPU (i.e., the bed) and work (anything outside of sleep) (Exelmans & Van den Bulck, 2016; Moulin & Chung, 2017). The CPUser from any age group may be affected by the displacement of sleep, however, it appeared to be highest in young adolescents **(**Hysing et al., 2015)**.**

Arousal theory is based on the fact that the use of electronic media such as cell phones just before sleep may increase mental (cognitive), emotional or psychological arousal (Cain & Gradisar, 2010). Such arousal may happen due to violent and sexual media content (Brown et al., 2006; Dill, Gentile, Richter, & Dill, 2005). The media content (arousal hypothesis) concept can also be illustrated by mental (cognitive), emotional and/or psychological arousal as the brain takes time to prepare for sleep after screen time (Clayton et al., 2015; Matar Boumosleh & Jaalouk, 2017). Screen time may include video gaming, online chatting, internet browsing (shopping, surfing, scrolling, etc.), social networking, and watching videos. Playing video games before sleep also results in reduced sleep quality, longer sleep latency, and poor memory performance (King et al., 2013; Dworak, Schierl, Bruns, & Struder, 2007; Weaver, Gradisar, Dohnt, Lovato, & Douglas, 2010), however, CPU for unstructured leisure, especially in bed, affects sleep variables substantially (Exelmans & Van den Bulck, 2016). In sum, interacting with cell phones before sleep may increase emotional and/or mental (cognitive) arousal, which might lead to sleep latency, sleep disruption, and poor sleep quality.

Hormonal secretion, i.e., melatonin suppression, is the biological aspect of sleep disruption and was tested through several clinical trials in previous studies. However, sleep displacement and arousal are the psychological (mental/emotional) aspects of sleep quality and were not previously investigated. The presented study, therefore, will focus on these psychological aspects and will investigate sleep displacement and arousal mechanisms of sleep disruption.

2.3.5. Summary

CPU of young adults, from the different time of the day and night, negatively impact sleep quality. Constant connection with a cell phone creates various sleep-related physical and mental disorders. Cell phone operations such as texting, calling, or social media keep young adults engaged for long hours, which can leave them with sleep dysfunction and sleep deprivation. The high frequency of CPU causes several sleep disorders in young adults, however, CPU with current cell phone applications may influence sleep quality differently. Therefore, there is a need to investigate the relationship between CPU, with current cell phone applications, and sleep quality of young adults from the current population.

2.4. CPU and Academic Performance

2.4.1. Brief overview

Investigating the impact of CPU on young adults' academic performance is imperative because internet-connected cell phones are the integral component of their day-to-day life. Moreover, collegiate young adults are in constant connection with their cell phones, even during class and/or study time. Cell phones have emerged as all-in-one compact electronic devices over the last two decades and have allowed users to work on multiple applications at one time. It is anticipated that CPU would help improve performance measures, however, hinder learning inside and outside the classrooms, thereby acting as a bad element for improving academic performance. Nevertheless, CPU acts as a good element for academic performance when used for learning. Overall, CPU may be good or bad for academic performance in various ways but needs to be understood using current cell phone operations for a current young adult population.

The outcomes of existing studies pertaining to CPU and academic performance portrays an ambiguous and inconsistent picture altogether. The literature review conducted to support this argument will be delineated in four sections in order to clarify how CPU and academic performance were studied in the previous literature. The first section will describe relevant prevalences and scope data on CPU and academic performance of young adults, the second section will describe the existing relationship between the two variables, the third section will describe underlying theories, and the fourth section will summarize the literature review.

2.4.2. Relevant Prevalence and Scope Data Concerning CPU and Academic Performance

Over two-thirds of college students use some sort of electronic devices, including cell phones, to complete their academic tasks (Jacobsen & Forste, 2011). College students have a positive outlook on cell phones as these devices provide the flexibility of time and place in achieving academic goals with little or no effort (Tossell et al., 2015). However, Elder (2013) found that college students were neutral about their in-class-CPU. In another experimental study, a treatment group, i. e., a group of college students who were allowed to text during class lectures, were found to perform worse than the control group (Gingerich & Lineweaver, 2014). These results indicate that college students are somewhat aware of the harmful effects of in-class CPU, particularly of texting, but few of them (8%) realize that it can impede their academic achievements (Froese et al., 2012; Berry & Westfall, 2015).

For college students, cell phones are equally important as that of other learning tools such as textbooks. Almost all college students bring their cell phones to class (Tindell & Bohlander, 2012), but the majority of them put these devices on “vibrate” or on “silent” mode (Berry & Westfall, 2015). Authors Pettijohn, Frazier, Rieser, Vaughn, and Hupp-Wilds (2015) have found that college students leave the classroom just to check text messages, however, this percentage was not very high. Further, Pettijohn et al., (2015) concluded that, from 10.3% of students who leave the classroom for one or the other reasons, “32% indicated that they had an emergency and 24% indicated they were bored or just ‘had to check’ (p. 515)”. The study also mentions other responses such as work, business, or to avoid disturbing the class for leaving the classroom to check cell phones. These studies suggest that carrying a cell phone to the classrooms create an option for collegiate young adults to get involved with something other than class and/or study, however, advantages such as using cell phones for an emergency cannot be ruled out.

Classroom CPU may be distracting for the primary user as well as for others. Although a majority of college students (90 - 97%) are aware of their classmates’ CPU (Berry & Westfall, 2015), most of them, approximately 77%, were not bothered by it (Pettijohn et al., 2015). College students spend around 2.69 minutes texting during a six-minute classroom simulation presentation and perform 27% worse than that of nontexters on a quiz on lecture material (Froese et al., 2012). Academic achievements of college students were found to be reduced by 6.3 points, on a scale ranging from 0 to 100, for every 100 minutes of CPU, and the impact of CPU during class/study time was almost double than that of CPU outside/free time (Felisoni & Godoi, 2018).

College students often switch from class and/or study to check cell phone notifications (Rosen et al., 2013). Such frequent switches add-up and leads to increased CPU hours per day. Increased number of daily CPU hours resulted in poor academic performance, even during the first year of college (Jacobsen & Forste, 2011). Authors Jacobsen and Forste (2011) have found notifications from texting, social media, and gaming as the key contributors of daily CPU hours. In fact, texting and social networking affected academic achievement the most. For example, in a study, texting and Facebook'ing (checking Facebook regularly), during academic tasks negatively affected overall GPA of college students (Junco & Cotton, 2012). Moreover, frequently checking cell phone notifications, spending long hours on texting, social networking and gaming are the potential causes of declining academic performance of young adults (Hong et al., 2012; Rosen et al., 2013). However, social media usage, such as Facebook'ing and Twitter'ing, impacts GPA more severely than that of texting (Bjornsen & Archer, 2015), as college students spend more time on social media (Wood, 2018).

Prevalence and scope data on CPU indicated that current cell phones possess numerous operations and Apps that are highly engaging. With these operations and

Apps, cell phones can occupy a significant amount of time meant for academic activities, thereby, leaving young adults with low academic achievements.

2.4.3. Existing Relationships between CPU and Academic Performance

Various aspects of CPU were recognized to negatively impact academic performance, including multitasking (Junco & Cotton, 2012; Lawson & Henderson, 2015). A large number of cell phone features, increasing at a rapid rate, were recognized as key factors that promoted classroom multitasking behaviors (Jacobsen & Forste, 2011; Bjornsen & Archer, 2015; Lawson & Henderson, 2015). When multitasking during studying, task-switching inside or outside of the classrooms was another key reason for the declining academic performance of high CPUsers (Rosen et al., 2013; Wood et al., 2012). "All of the media-related technologies associated with increases in multi-tasking and decreases in academic performance are now commonly accessed with a single, Internet-connected cell phone," says authors Lepp, Barkley, and Karpinski (2014) who examined CPU and academic performance of college students.

The CPU based multitasking behaviors, apart from other multitasking behaviors such as talking to peers on off-class topics and working on off-class assignments, negatively influenced academic performance (Junco & Cotton, 2012; Wood et al., 2012). CPU multitasking includes texting, calling, browsing the internet, social networking, or any other activity involving cell phones. Academic performance of high media multitaskers is lower than that of low media multitaskers because they use multiple digital media technologies outside the class while preparing for their exams (Patterson, 2016). Although, all cell phone operation may contribute to multitasking, texting alone was found to have a significant negative correlation with the actual GPA of college students (Lepp et al., 2014).

A group of researchers was specifically concerned about the amount of time spent on cell phone activities as Lepp et al. (2014) said, “it may be that high-frequency cell phone users, in comparison to low-frequency users, spend less time focused on academic pursuits (i.e., attending class, completing homework assignments, and studying) because a larger portion of their time is consumed by CPUse” (p. 333). Lepp et al. (2015) also confirmed negative outcomes of CPU on academic performance through a consecutive study by controlling variables such as demographic information, self-efficacy, and high school GPA. They concluded that in-class CPU and CPU at night were negatively related with overall GPA of college students.

On the contrary, the increased familiarity of cell-phone-mediated-communication (CPMC) was found to have a positive influence on cell phone self-efficacy and on behavioral intentions (Han & Yi, 2018). CPMC enabled college students to perceive CPU for learning and thereby helped them to improve academic performance. However, students with less familiarity of using cell phones for learning had adverse effects on academic achievements. High CPU and familiarity of CPMC for learning may influence academic performance measures differently, nevertheless, the CPU of any type can harm academic performance if not rationalized for time and usage.

Use of cell phones inside and outside the classroom from different times and for different purposes may contribute to academic performance differently. For example, CPU during class/study impacts GPA negatively, however, CPU at night was found to be unrelated to academic performance (Li et al., 2015). Further, CPU per day influences performance measures differently because the daily in-class CPU is negatively associated with the test scores, irrespective of actual in-class CPU time (Bjornsen & Archer, 2015). It is clear that the use of cell phones during class and/or study time is detrimental to academic performance.

College students feel motivated for using cell phones for learning, and the majority of them (71%) believe that CPU for learning makes them more productive (Fernandez, 2018). Moreover, they believe that CPU enhances their learning processes, assists them with learning, and makes overall learning effective. However, excessive CPU disrupts learning inside and outside the academic setting, which leaves college students with low academic achievements (Bjornsen & Archer, 2015; Patterson, 2016). Besides, they spend an enormous amount of time using cell phones, with texting at the top. It was found that college students text within the classroom for three reasons: checking for emergencies, boredom, and resolving conflicts; however, most of them (89.7%) do not leave the classroom just to check their cell phone notifications (Pettijohn et al., 2015).

Existing studies have shown a negative correlation between CPU and academic performance. There are many reasons, CPU multitasking, task-switching, excessive

CPU, and less awareness of CPU for learning are a few of them. Research has also shown that cell phones, with various applications/functions, can be used as learning tools. However, using them during class and/or study time does not correlate positively with academic performance. Nevertheless, cell phones and CPU habits should be developed in a way that can benefit users, particularly from collegiate young adults because they have a positive belief about the use of cell phones for learning.

2.4.4. Underlying Theories

CPU during class and/or study time may compel young adults to switch between tasks like cell phone use and academic activities. According to switch-load theory, a two-stage model of executive control, there is a time loss, called switching-time cost, associated when one switches between the tasks (Rubinstein, Meyer, & Evans, 2001). Switching-cost (loss of efficiency caused due to task-switching) per switch may be relatively small but adds up to a large amount when switched between tasks multiple times. Task switching dilates response time, even when switching takes place between two predictable tasks, thereby decreasing productivity.

The model of executive control (Rubinstein et al., 2001) also suggested that there are two distinct and complementary stages, goal-shifting and rule-activation, involved in performing a task. Goal-shifting is shifting goals between current and future tasks whereas rule-activation is turning on the rules for a current task and turning off the rules for a prior task. The model was tested by an experimental study, comprising of four sets of experiments using math problems and geometric objects. It was found that there is a time loss, named switching-cost when switching between two tasks. Switching-cost significantly increases in cases of switching between complex tasks and is even greater for switching between relatively unfamiliar tasks (Rubinstein et al., 2001).

Self-regulated learning (SRL) theory “focuses attention on how students personally activate, alter, and sustain their learning practices in specific contexts” (Zimmerman, 1986, p. 307). As per the theory, students need to be able to “control contextually specific cognitive, affective, and motoric learning processes” with “varying amounts of selectivity and structuring in order for them to learn.” This theory has progressed through three models i. e. Triadic Analysis model, Cyclical Phase model, and Multi-Level model (Zimmerman, 1986; Zimmermann, 2000; Zimmerman & Moylan, 2009). Triadic Analysis model of SRL was visualized as Bandura’s triadic model of social cognition that described the interaction between environment, behavior, and the person itself (Zimmerman, 1989). Cyclical Phase model described how metacognitive and motivational processes interrelate whereas, Multi-Level model depicted the stages of acquiring self-regulatory competency.

Zimmermann and Martinez-Pons (1986) have identified various categories of SRL strategies, which were found to be closely related to academic achievements. These strategies included metacognitive (plan, organize, self-instruct, self-monitor, and self-evaluate), motivational (perceiving themselves as competent, self-efficacious, and autonomous), and behavioral (select, structure, and create environments) processes that help students to actively participate in their own learning (Zimmerman, 1989). Various cell phone operations may help young adults in implementing these SRL strategies during class and study, which may further regulate their metacognitive, motivational, and behavioral learning processes and thereby may lead to better academic performance.

2.4.5. Summary

The CPU of young adults is correlated with academic performance but the relationship varies (Mendoza et al., 2018; Felisoni & Godoi, 2018; Han & Yi, 2018; Lepp et al., 2015; Lepp et al., 2013). CPU was also found as one of the defining characteristics of the current generation of young adults (Smith, Raine, & Zickuhr, 2011; Tindell & Bohlander, 2012), however, the relationship between CPU and academic performance was found to be contradictory. For example, CPU was found to be negatively (Lepp et al., 2015; Lepp et al., 2014), positively (Han & Yi, 2018), and not associated (Elder, 2013) with academic performance.

Texting was found to impact academic performance the most (Lepp et al., 2014; Gingerich & Lineweaver, 2014; Froese et al., 2012), however, social media such as Facebook and Twitter affected academic performance more adversely than that of in-class texting (Bjornsen & Archer, 2015). It is, therefore, necessary to investigate the relationship between CPU and academic performance of college students from the current population. The outcomes of existing studies pertaining to CPU and academic performance of young adults are inconsistent and further research is required in this area using instruments with the latest CPU operations and samples from the current young adult population.

2.5. CPU and Psychological Well-Being (PWB)

2.5.1. Brief overview

Because of the physical and mental health risks associated with CPU, it is crucial to understand how the CPU of young adults affects PWB. Physical and mental health variables are associated with PWB, a key component of overall well-being. Basic cell phone operations such as calling and texting were studied with mental health outcomes such as sleep disturbance and symptoms of depression at the beginning of this decade (Thomée et al., 2011). The study from Thomée et al. (2011) heavily revolved around general health outcomes, however, sleep disorders were at the core because the poor sleep quality was found to be causing physical and mental health problems. It is yet unknown how the CPU affect PWB of young adults.

The literature review conducted on the current status of research on CPU and PWB is covered in four sections: relevant prevalence and scope data on CPU and PWB, the existing relationship between CPU and PWB, underlying theories/principles, and summary.

2.5.2. Relevant Prevalence and Scope Data Concerning CPU and PWB

It is a well-substantiated fact that CPU-affected sleep quality, directly or indirectly, influences the physical and mental health of young adults, which may further affect their judgments of life. Life-judgments determine satisfaction with life, one of the three components of subjective well-being (Diener, 1984; Andrews & Withey, 1976), and may serve as a crucial factor for well-being. In previous studies, a satisfaction-with-life scale was used to investigate the subjective well-being of young adults (Diener, Emmons, Larsen & Griffin, 1985). However, a flourishing scale, a new well-being scale that includes both emotional and psychological aspects of well-being does not measure subjective well-being independently (Diner et al., 2009a; Diner et al., 2009b).

PWB is based on effective human functioning. Effective human functioning consists of various aspects of personal and professional achievements. These aspects include engagement and connectedness, competency and accomplishment, pleasure and sense of enjoyment, sense of purpose and fulfillment, sense of belonging and acceptance, and optimism about the future ((Diner et al., 2009a). The achievement aspects also include the feeling of belongingness including affiliation, social interaction, friendship, giving and receiving, and contributions to the well-being of others (Maslow, 1987). Authors Diener et al. (2009b) say that studying only the cognitive and emotional aspects of well-being objectively wouldn't suffice; therefore the aspects of achievement need to be investigated as well. Likewise, the impact of CPU on the aspects of personal and professional achievements cannot be ruled out.

2.5.3. Existing Relationships between CPU and PWB

In the literature review, only one study (Kumcagiz & Gunduz, 2016) appeared that claimed to measure PWB of young adults by using the PWB scale, however, it investigated the relationship between levels of PWB and smartphone addiction. The study found that smartphone addiction was significantly associated with the levels of PWB and inferred that high smartphone users have lower levels of PWB than that of low smartphone users. Several factors such as socio-demographic characteristics (gender and grade levels) and perception (of academic achievements, of socio-economic status, and of parents attitudes) were also found to be associated with the levels of PWB of young adults.

In addition, two articles (Lepp et al, 2014; Li et al., 2015) were found that investigated the relationship between CPU and subjective well-being of young adults. In the first study, Lepp et al. (2014) investigated the impact of texting on subjective well-being. Lepp et al. (2014) also found that the CPU of college students was correlated with satisfaction of life through several intervening variables such as academic performance and anxiety. The study concluded that CPU influenced subjective well-being, however, the study did not examine a direct link between the two. In the second study, Li et al. (2015) examined how cell phone dependency on the locus of control ("individuals' belief about their ability to control the environment as well as outcomes of their behavior," p. 450) influenced satisfaction with life. Li et al. (2015) found that college students with a high internal locus of control are less vulnerable to CPU and thus have better sleep quality and improved academic performance, which, in turn, increases their satisfaction with life.

A cross-reference (Chan, 2013) emerged in the literature, which examined the impact of communicative (i. e. calling, texting, social media, and emails) and non-communicative (i. e. information seeking activities, listening to music, playing games, and taking photo or record videos) uses of cell phones on subjective well-being. The outcomes of the study showed that cell phone voice communication directly related to well-being whereas online communication inversely related to well-being. Further, excessive non-communicative uses of cell phones were found to be inversely associated with a positive effect. Nevertheless, Chen and Li (2017) have found communicative CPUses to affect PWB positively through bonding and bridging social capital.

Another study (Park & Lee, 2012) was found that investigated motives of CPU and the impact of these motives on PWB variables such as loneliness and depressive symptoms. The study concluded that socio-psychological prosperity of more extroverted CPUsers is high as they have increased psychological benefits compared to that of less extroverted users. Further, caring for others, one of the motives of CPU, was found to be negatively associated with PWB variables such as loneliness and depression, which, in fact, is good for improved social relationships.

One further study conducted by authors Hoffner and Lee (2015) investigated the impact of CPU on well-being through an associated variable such as emotion regulation. The study revealed that well-being is positively associated with the use of cell phones for emotion regulation. CPU and perceived effectiveness of CPU for emotion regulation were also found to be correlated. The study concluded that different CPUses may result in various psychological benefits as the feeling of connectedness is one of the key factors in well-being.

2.5.4. Underlying Theories

CPU may be associated with the different states of effective human functioning that were described by different theorists and are as follows: meaning and purpose, supportive and rewarding relationships, engaged and interested, contributes to the well-being of others, competency, self-acceptance, optimism, being respected (Ryff, 1989; Deci, 2000; 2001). The states, such as, the feeling of engagement and interest, pleasure, and meaning and purpose (Seligman, 2002) may also have a correlation with the use of cell phones. In previous studies, engagement and flow were recognized as the core components of well-being and psychological capital (Csikszentmihalyi, 1990), which may be linked to CPU.

The features of positive psychological functioning, described by previous theorists, constituted the core dimensions of the theory of psychological well-being proposed by Ryff (1989). As per the theory, six theory-guided dimensions constitute positive psychological functioning. Kumcagiz and Gunduz (2016) have recently referred to this six-dimensional theory and stated that "psychological well-being is closely related to self-acceptance, positive relations with others, autonomy, environmental mastery, purpose in life, and personal growth besides healthy physiology without stress and other mental problems" (Ryff, 1989). Optimism was considered one of the key factors of positive and healthy functioning (Peterson & Seligman, 2004). Cell phone social networking (CPSN) may help young adults to become involved in activities that they find meaningful and purposeful, and thereby help them feel engaged and interested.

Young adults may also find CPSN meaningful and purposeful as they feel optimistic about CPSN-based social relationships.

A positive social relationship is defined by both having support from others and by being supportive of others, individually or in a community (Ryff, 1989; Ryan & Deci, 2000). Supportive and rewarding social relationships were viewed as one of the key components of mental health (Ryff, 1989). Thus, having positive and supportive relations with others in society and communities were always important ingredients of PWB theories. Use of cell phones for social media may help young adults to fulfill their psychological needs (i. e., esteem needs and belongingness and love needs). The feeling of belongingness and accomplishments are the psychological needs that include love, belonging, and esteem needs and are described by third and fourth levels of Maslow hierarchy of needs ("Maslow's Hierarchy of Needs," 2018; Maslow, 1987). The third level involves the feeling of belongingness such as affiliation, social interaction, friendship, giving and receiving, etc. The fourth level involves the feeling of accomplishment. The giving and the receiving components of the feeling of belongingness further contribute to the happiness and well-being of others.

Providing social support to others was found to be more important to health and well-being than receiving support (Brown, Nesse, Vinokur, & Smith, 2003). Brown et al. (2003) found that “mortality was significantly reduced for individuals who reported providing instrumental support to friends, relatives, and neighbors, and individuals who reported providing emotional support to their spouse (p. 320).” The study thereby articulated ‘giving support’ as a key component of interpersonal relationships and well-being. Dunn, Akin, and Norton (2008) found that spending one’s income on others had a positive impact on happiness and well-being. The study further concluded that giving to others provides more happiness than that of receiving from others. Cell phones may help young adults to contribute to the happiness and well-being of others when providing support on social media thereby fulfilling their psychological needs.

2.5.5. Summary

High CPU, as a whole, was found to result in depression and anxiety in young adults (Adams & Kisler, 2013; Moulin & Chung, 2017). Some studies have reported depression as one of the key factors, which were affected by high CPU (Demirci et al., 2015; Eyvazlou et al., 2016; Tao et al., 2017). In the previous studies, an indirect relationship between CPU and subjective well-being was investigated. The relationships between CPU and well-being variables such as physical and mental health outcomes were also investigated through intervening variables. The purpose of CPU based research was to explore the ways CPU affects the overall well-being of young adults, however, it was not completely fulfilled. CPU may or may not have a direct influence on PWB of young adults, however, this was not previously examined. It can be concluded from existing literature that a study examining CPU and PWB of the current young adult population is pertinent.

2.6. Research Hypotheses

Given the reasoning above on how CPU may influence sleep quality, academic performance, and PWB, the present study is proposed to test the relationship between CPU and each of the three outcome variables reviewed. The multiple hypotheses of the proposed study are stated as follows:

H1a: We expect, according to sleep displacement theory, the CPU for unstructured leisure activities before sleep to relate positively to the sleep latency of undergraduate students;

H1b: We expect, according to arousal theory (media content), CPU for accessing sexually explicit, violently, or emotionally charged media content before sleep to relate positively to the sleep difficulty (sleep disturbance) of undergraduate students;

H2a: We expect, according to the switch-load theory, the frequency of cell phone checking during a class/lecture, lab and/or study session to negatively relate to the academic performance (GPA) of undergraduate students;

H2b: We expect, according to Zimmerman theory of self-regulated learning (SRL), the use of cell phones for self-regulated strategies (metacognitive, motivational, and behavioral) to relate positively to academic performance (i.e., college GPA) of undergraduate students;

H3a: We expect, according to humanistic theories of positive functioning, cell phone social media feelings to relate positively (due to anytime anywhere accessibility of cell phones) to the PWB of undergraduate students;

H3b: We expect, according to Maslow's hierarchy of needs (psychological needs i. e. belonging and esteem needs), instant cell phone social media responses (likes, shares, and comments followed by emoji's, GIF's [Graphics Interchange Format images] or stickers) to relate positively to the PWB of undergraduate students.

3. RESEARCH METHODS

3.1. Research Context

This study shall be conducted at Texas A&M University (TAMU). TAMU is a large public research university with 68,390 enrolled in 2019 from which the undergraduate enrollments were 53,791 with 47.02% Female ("Common Data Set 2019-2020," 2019). This large enrollment comprised of students from all racial/ethnic category, i.e., Hispanic/Latino (24.8%), Black or African American (2.6%), White (59%), American Indian or Alaska Native (0.2%), Asian (8.5%), and Native Hawaiian (0.06%). A sample from such a diverse setting will increase the generalizability of the study outcomes. In addition, collecting data from various majors will help analyze the impact of CPU on sleep quality, academic performance, and PWB across the samples. This will open new vistas of research for future studies.

3.2. Participants

The study participants will include recruitment from enrolled undergraduate students at the time of taking the survey from different subject majors at Texas A&M University located in College Station, TX.

3.2.1. Recruitment

All enrolled undergraduate students will be invited for voluntary participation by email invitations (Appendix A) distributed through the university's listserv. The invitation emails will be distributed to prospective subjects to ensure that each individual within the chosen population is selected by chance and is equally as likely to be picked as anyone else. Before recruiting participants, permission will be obtained from the Texas A&M University Institutional Review Board (IRB) and TAMU listserv (listserv.tamu.edu).

The link on the invitation email will take the invitees to the TAMU Qualtrics webpage. This webpage will have informed consent, required from undergraduate students, on the first page. Prospective participants will be able to read all the necessary information regarding their participation in the study before electronically signing the informed consent (Appendix B). This consent will affirm that their participation in the study is voluntary and withdrawal at any time is accepted without comment or penalty. The decision of undergraduate students to participate will have no influence on their grades and their current or future relationship with the university Those who submit their informed consent by clicking the "I Agree" button will have access to the survey.

3.2.2. Sampling

For this study, convenience sampling method will be adopted with probability measures enacted to ensure an equal opportunity for every student to participate. Participants from the targeted population who complete the Qualtrics survey will comprise the sample for the study. Although convenience sampling is not the ideal method of obtaining a complete representative sample in a quantitative study, the target population of this study will likely share many of the same characteristics because they are all classified as undergraduate students enrolled for a semester at a university.

However, there remains the possibility that those who return the informed consent and complete the survey will exhibit individual characteristics that might lead to an unintended bias.

3.2.3. Ethics & confidentiality

Ethically, participation in this study poses no greater risk than participants would encounter in everyday life. However, if the participant feels as if some questions that are asked are stressful or inappropriate, they have the option to opt out of the survey. Information about individuals and/or organizations that may help participants with any concerns will be provided. The information about participants will be kept confidential to the extent permitted or required by the law. No identifiers linking them to this study will be included in any report that might be published.

Research records will be stored securely in a password-protected computer file that only the researchers (that includes me, the committee Chair and co-Chair) will have access to. Apart from this, only research personnel representatives of regulatory agencies (e.g., Office of Human Research Protections (OHRP), and Texas A&M University Human Subjects Protection Program) will have the access to their information in order to ensure that the study is being run ethically. The participants will be provided the researcher's contact information for any further questions or concerns.

3.3. Instrumentation

A reliable and valid instrument (Appendix C) comprising of scales from existing studies will be used to measure the study variables. Only scales that are written in English will be considered for the purpose of data collection.

3.3.1. Dependent Variables

3.3.1.1. Sleep Quality

To measure sleep quality, a 19 item Pittsburgh Sleep Quality Index (PSQI) scale will be used (Appendix C). The PSQI scale is a standardized clinical instrument, which has strong internal consistency (Cronbach's alpha = 0.83) and equally good test-retest reliability ($r = 0.85$) (Buysse et al., 1989). This scale was developed by keeping all the quantitative aspects of sleep in mind and was meant to discriminate between ‘good’ and ‘poor’ sleepers. In addition to that, PSQI helps to provide an easily interpretable clinical assessment of the different aspects of sleep quality. Recently, the structural validity of PSQI was evaluated with a large non-clinical sample, ($n = 2189$) and it was observed that “a three-factor model (i.e., sleep efficiency, sleep latency, and sleep quality) was better fit than the commonly used single-factor structure” (Jia, Chen, Deutz, Bukkapatnam, & Woltering, 2018). Also, the study “recommended the use of three separate factors to assess sleep quality,” which will help support the claim of examining sleep latency and sleep disturbance in the current study.

3.3.1.2. Academic Performance

In this study, self-reported GPA will be used to assess the academic performance of undergraduate students (Appendix C) as these were found to be valid measures of academic performance in a crucial meta-analysis conducted by Kuncel, Credé, and Thomas (2005) on the validity of self-reported GPA. It was also observed that “students with lower levels of cognitive ability (as measured by standardized admissions tests) tend to report their GPAs less reliably” (p. 74). Self-reported GPA will also be an appropriate estimate of the academic performance of college students as “there were no large differences in the validity of self-reported GPA of males and females” (Kuncel et al., 2005, p. 72).

The meta-analysis mentioned two reasons of misrepresenting self-reported scores: “either the respondents did not believe what they were told by the parties requesting self-reported grades, or they felt that they would gain something by misrepresenting their GPA, such as protecting their pride or self-respect” (p. 77). The current study may also get intentionally inflated scores, nevertheless, suitable measures will be taken to reduce any such probability. First, it will be clear to the participants that their GPA will be purely self-reported and that they will have no gain from misrepresenting it. Likely, no identifiers will be collected from the participants to reduce this effect. Second, participants will have no direct benefits except raising awareness. High school GPA will be used for incoming freshmen as high school “self-reported grades were found to be highly positively correlated with actual grades in all academic subjects and across grades 9 to 11" (Sticca et al., 2017, p. 1).

3.3.1.3. Psychological Well-Being (PWB)

An 8 item Flourishing Scale (FS) (Cronbach's alpha = 0.87), developed by Diener et al. (2009b), will be used to measure PWB (Appendix C). With the help of Flourishing scale, the present study aims to examine the single PWB scores of undergraduate students. As per Diener et al. (2009b), the reliability and validity of this scale were tested using a large sample including participants from six different locations. Diener et al. (2009b) further claimed FS is a measure with good psychometric properties as "it correlated strongly with the summed scores for the other psychological well-being scales, at 0.78 and 0.73. Thus, the FS yields a good assessment of overall self-reported psychological well-being, although it does not assess the individual components of social–psychological well-being" (p. 152).

The psychometric properties of the FS scale were also determined in other studies, further supporting the use of this particular scale for the current study. The Cronbach alpha coefficient of FS was found to be 0.80 in a study conducted with a sample of 529 pre-service teachers to evaluate the reliability and validity of a translated version of the FS (Telef, 2013). This study was also important because "test-retest scores showed that there was a high level of a positive and meaningful relationship between the first and second applications of the scale ($r = 0.86$, $p<0.01$)" (p. 384). The psychometric properties of FS were assessed recently with a sample of 408 university students and the

Cronbach's alpha coefficient was found to be 0.87 (Kumcagiz & Gunduz, 2016), which supports the claim of using it a reliable and valid scale to test PWB of young adults.

3.3.2. Independent variable

This section provides a comprehensive explanation of the reliability and validity of each item/construct of the instrument used in the present study

3.3.2.1. Cell Phone Use

The CPU scale used for the current study consisted of no new original items. Items used in individual constructs were adapted from existing validated scales and were modified as per the requirements of the study. Some items were extended. A few linguistic changes were also made in the items to make them more clear and understandable. A detailed construct-wide description of all the items, along with the modifications and linguistic changes, will be presented in the following sections in terms of i) items/scales used, ii) reliability and validity evidence, iii) nature of adaptation, and iv) experimenter added questions. The researcher and his co-chairs reviewed the items to evaluate the overall fitting of the items/constructs to the present study. The researcher has also reviewed the questionnaire with a writing consultant who was a doctoral candidate from the department of English.

The CPU scale used in the present study consists of 46 items. There are a total of seven constructs in the scale: CPU_BeforeSleep; CPU_Arousal; CPU_Classroom (or CPU_Switch); CPU_SRLBehavior; CPU_SocialMediaFeelings; CPU_SocialMediaResponses; CPU_Total. Six constructs are compiled under three different bigger constructs (i.e., CPU nighttime, CPU academics, and CPU social media) that are aligned to the specific domains of the study; sleep quality, academic performance, and PWB. The sub-constructs for CPU nighttime are CPU_BeforeSleep and CPU_Arousal. The sub-constructs for CPU academics are CPU_Classroom (or CPU_Switch) and CPU_SRLBehavior. The sub-constructs for CPU social media are CPU_SocialMediaFeelings and CPU_SocialMediaResponses. The seventh construct, CPU_Total, is meant for providing a descriptive measure of the total amount of time spent on various cell phone activities.

Various steps were taken to test the translational validity (i.e., face validity and content validity) of the questionnaire. Drost (2011) describes translational validity as a type of validity, which “centres on whether the operationalization reflects the true meaning of the construct. Translation validity attempts to assess the degree to which constructs are accurately “translated” into the operationalization, using subjective judgment – face validity – and examining content domain – content validity.”

Face validity, often called 'common sense' approach (Shuttleworth, n.d.), is a superficial, however, important form of validity. As it was defined by Drost (2011), the “face validity is a subjective judgment on the operationalization of a construct.” To test the face validity, the survey was administered to two professional development specialists from the Texas Center for the Advancement of Literacy & Learning (TCALL). The feedback from both the specialists from TCALL were implemented in the instrument.

Content validity is defined as "a qualitative type of validity where the domain of the concept is made clear and the analyst judges whether the measures fully represent the domain (Bollen, 1989, p.185)." Faculty experts from the department of English and the department of Communication were contacted to review the final draft of the instrument. Two reviewers, one from each department, have reviewed the instrument for the following:

(i) Whether or not the items in the instrument effectively capture what was intended to measure.

(ii) Linguistic consistency and content validity of extended/modified items.

(iii) Overall alignment of the items within constructs, as well as within the overall instrument, when brought together in one scale.

All the items in the instrument were clear on content validity measures in terms of their intent and inclusiveness; one of the reviewers stated, "this [the instrument] seems pretty comprehensive and very clear in its intent and uses standard question formats."

The principal component factor analysis was conducted for the items. The Kaiser-Meyer-Olkin (KMO) measures of sampling adequacy were determined for all six constructs and it was observed that all the items loaded well within the designated constructs (see Appendix E, for more detail). Two pilot studies [Study 1 (Spring 2019; n=32; undergraduate students; 78% female); Study 2 (Fall 2019; n=78; undergraduate students; 84% female)] were conducted to gauge various factors including the time required for completion of the survey. All constructs were found to exhibit good internal consistency [Cronbach's alpha = 0.87 (Study 1); Cronbach's alpha = 0.86 (Study 2)]. Reliability was tested further using the data from the main study (N = 525; 75.4% female) and the instrument was found to exhibit good internal consistency (Cronbach's alpha = 0.89).

The item level description of validity and reliability of the instrument is provided in the following sections.

3.3.2.1.1. CPU_Nighttime

3.3.2.1.1.1. Number of items: 15

There are two sub-constructs of CPU_Nighttime as follows:

(i) CPU_BeforeSleep

There are nine items on a Likert scale from '*never*' to '*always*' in this construct to estimate the use of cell phone before sleep. These items determine whether participants have awakened after going to bed (or stayed up late after a target bedtime) due to the following cell phone operations/activities: calling, texting, checking notifications, emailing, listening to Podcasts, listening to music, social networking, watching videos (Netflix, Hulu, etc.), gaming, and non-social-media internet browsing (shopping, surfing, etc.). Participants ranked their use on a 4-point Likert scale and total score on the instrument range from 9 to 36 with higher score indicating higher CPU before sleep. All items in this construct displayed a good internal consistency (Cronbach alpha = 0.83) for the pilot study.

(ii) CPU_Arousal

There are six items in this construct. The first three items were meant to assess participants' engagement with their cell phones on a Likert-based scale (from *1* to *10*) towards emotionally charged texts and messages, explicit content pertaining to sexuality (pornography, tinder, dating sites, etc.), and explicit content pertaining to violence (video games, movies, etc.). The remaining three items, on a Likert-based scale (from *1* to *10*), were intended to assess the rate of occurrence of uses mentioned in the first three items that keep participants awake. Participants ranked their use on scale ranging from 1 to 10 and total score ranged from 6 to 60 with a higher score indicating extremely common to engage in emotionally charged texts and images and explicit content pertaining to sexuality and violence with the constant occurrence of being awake by engaging in these activities. All the items from this construct possessed good internal consistency (Cronbach alpha = 0.71) for the pilot study.

3.3.2.1.1.2. Item(s)/Instrument/Scale Used

(i) CPU_BeforeSleep

CPU_Night Scale (Li et al., 2015).

(ii) CPU_Arousal

Sexual Media Diet (SMD) Scale (Brown et al., 2006), sexting item (Fleschler Peskin et al., 2013), items for activities to engage in explicit content pertaining to sexuality and violence (Dill, Gentile, Richter, & Dill, 2005).

3.3.2.1.1.3. Reliability and Validity Evidence

(i) CPU_BeforeSleep

Internal consistency of the CPU_Night Scale used by Li et al. was tested for item analysis, and the scale was reported to possess good psychometric properties (Cronbach's alpha = 0.81). The validity of the CPU_Night Scale can be described by referring to its origin. The CPU_Night Scale was derived from a questionnaire originally developed and validated by authors Thomee et al. (2011). Thomee et al. developed a baseline questionnaire by collecting information on various cell phone usages and on other qualitative aspects of nighttime CPU. The cell phone usage variable was found to have a good correlation with original calls and text variables ($r = 0.73$, $p < 0.0001$, and $r = 0.84$, $p < 0.0001$, respectively).

(ii) CPU_Arousal

The base question regarding engagements in an arousal activity (Brown et al., 2006) has gone through a rigorous content analysis procedure. The content of the scale was based on the results from a media survey that comprised of television shows, movies, music, and magazines. Each unit from all four media was analyzed for its content, and detailed content analysis for the whole scale was provided in a separate study (Pardun, L'Engle, & Brown, 2005).

The validity of items used for sexting (i. e., emotionally charged texts and messages) (Fleschler Peskin et al., 2013), and the activities to engage in explicit content pertaining to sexuality and violence (Dill, Gentile, Richter, & Dill, 2005) were tested in previous studies. For example, sexting items used by Fleschler Peskin et al. were taken from a national campaign survey of teens and young adults in the United States ("National Campaign to Prevent Teen and Unplanned Pregnancy and Cosmogirl.com. Sex and tech: results from a survey of teens and young adults," n.d.). Dill et al. (2005) have provided a detailed content analysis of the items used for engaging with explicit content pertaining to *se*xuality and violence in video games. All the CPU_Nighttime items were found to possess a good internal consistency (Cronbach alpha = 0.77) for the pilot study.

3.3.2.1.1.4. Nature of Adaptation

(i) CPU_BeforeSleep

To measure the use of cell phone before sleep, 8 items were adapted from a CPU_Night Scale (Li et al., 2015), and one item was written by the researcher in similar lines as that of other items to gauge the disruption due to cell phone notifications after going to bed at night. Li et al. employed a 5-point Likert scale (i.e., 1 - "Never", 2 - "Only Occasionally", 3 - "Occasionally", 4 - "Often", and 5 - "Always"). To have clarity in responses, one point (i.e., 2 - "Only Occasionally") was removed for the present study, which resulted in a revised 4-point Likert scale.

A few modifications were made to the original items in terms of including more cell phone activities, such as listening to Podcasts. Some minor linguistic alterations were also made to some of the items to make the meaning of those items clearer. For example “sending or receiving” was mentioned in parentheses for texts, “receiving, writing, sending" for emails, "Shopping, surfing, etc." for internet browsing, and "Instagram, Twitter, Snapchat, Facebook, LinkedIn, etc." for social media CPU.

(ii) CPU_Arousal

The items measuring nighttime arousal were drawn from various sources. A base question regarding engagements in an arousal activity was adapted from the Sexual Media Diet (SMD) Scale developed by Brown et al. (2006) (Cronbach alpha = 0.83). The SMD scale was constructed to capture "the overall proportion of sexual content in the adolescents' media diet in 4 media over a 1-month period at baseline." The base question from Brown et al. (2006) was modified and was extended to six items by the researcher, mirroring the CPU_BeforeSleep items derived from Li et al. (2015). The cell phone operation/activity sexting (i. e., emotionally charged texts and messages) was adapted from Fleschler Peskin et al. (2013), and the activities to engage in explicit content pertaining to sexuality and violence were adapted from Dill, Gentile, Richter, and Dill (2005).

3.3.2.1.1.5. Experimenter-added Questions

(i) CPU_BeforeSleep

For the present study, one item was written by the researcher along lines similar to that of the original items to assess if the CPUsers are awakened by the cell phone notifications after going to bed at night. The item is as follows:

In the last 30 days, have you been awakened by cell phone notifications after going to bed at night?

Never Occasionally Often Always

(ii) CPU_Arousal

For the present study, six items were written by the researcher along lines similar to that of the original items to assess the arousal due to the use of cell phones. These items are as follows

(i) In the last 30 days, how common is it for you to use your cell phone to engage in:

(1 = not common at all / 10 = extremely common)

(a) emotionally charged text messages and images

1 2 3 4 5 6 7 8 9 10

(b) explicit content pertaining to sexuality (pornography, tinder, dating sites, etc.)

1 2 3 4 5 6 7 8 9 10

(c) explicit content pertaining to violence (video games, movies, etc.)

1 2 3 4 5 6 7 8 9 10

(ii) In the last 30 days, rate how common it is for you to be kept awake by engaging in the following cell phone activities OR by thinking about occurrences earlier in the day

(1 = not common at all / 10 = extremely common)

(a) Reading or responding to emotionally charged text messages and images

1 2 3 4 5 6 7 8 9 10

(b) Sexually-oriented apps, multimedia, or related materials

1 2 3 4 5 6 7 8 9 10

(c) Violence-based apps, games, multimedia, or related materials

1 2 3 4 5 6 7 8 9 10

3.3.2.1.2. CPU_Academic

3.3.2.1.2.1. Number of items: 19

There are two sub-constructs of CPU_Academic as follows:

(i) CPU_Classroom (CPU_Switch)

There are ten items in CPU_Switch, the first construct, to measure the use of cell phones during class and/or study time. These items will measure the frequency of checking and responding to various cell phone operations/activities, such as texting, emailing, social networking, internet browsing, etc., on a ratio-based scale (from 0 to 40). The average of the items provide a total score for CPU_Switch. All the items from this construct were found to hold a good internal consistency (Cronbach alpha = 0.92) for the pilot study.

(ii) CPU_SRLBehavior

There are nine items in this construct to measure the use of cell phones for self-regulated learning behaviors, such as the use of an alarm, calendar, notes, timer, search engine, Google Docs, email or social media, texts, and calculator (CPU_SRLBehavior). These items were based on a Likert-based scale from ‘never’ to ‘always’ (1-“Never,” 2-

"Occasionally," 3-"Often," and 4-“Always”), and will assess CPU for self-regulated learning behaviors on a daily basis. The average of the items provided a total score for CPU_SRLBehavior. All the items from this construct hold a good internal consistency (Cronbach alpha = 0.87).

3.3.2.1.2.2. Instrument/Scale Used

(i) CPU_Classroom (CPU_Switch)

CPU_Classroom items from Li et al. (2015), CPU_Classroom items (Elder, 2013; Bjornsen and Archer, 2015).

(ii) CPU_SRLBehavior

Self-regulated Learning with Technology at the University (SRLTU) Scale (Yot-Domínguez & Marcelo, 2017), Self-Efficacy Scale for self-regulated learning (Zimmerman, Bandura, and Martinez-Pons, 1992), items associated with smartphone self-efficacy and behavioral intentions to use smartphones (Han & Yi, 2018).

3.3.2.1.2.3. Reliability and Validity Evidence

(i) CPU_Classroom (CPU_Switch)

The validity of adapted items can be described by the methods used to develop and validate these items in the respective source studies. Elder (2015) has created a scale of six items appropriate to measure students’ frequency of CPU in the classroom from an instrument of 30 items created for the whole study. Elder developed these CPU classroom items during an on-campus undergraduate class and tested them for validity on a Likert scale. These items were also reported to possess good internal consistency

(Cronbach's alpha = 0.75). Bjornsen and Archer (2015) created items to assess the frequency of CPU during the class, however, have not reported the psychometric properties of the items. The CPU classroom items from Li et al. (2015) were created and reviewed by the research team and were tested for internal consistency.

(ii) CPU_SRLBehavior

The instrument used by Han and Yi was developed by one of the authors from previous studies and was tested for reliability and validity. Two measures were taken to test the validity of the instrument. First, four faculty members assessed the instrument. Second, a pilot survey was administered for a small sample (n=10). The instrument was revised and changes were made to improve the items. This instrument comprised of four constructs, and all these constructs possessed good internal consistency (Cronbach's alpha ranging from 0.843 to 0.929).

The validity of the Self-regulated Learning with Technology at the University (SRLTU) scale (Yot-Domínguez & Marcelo, 2017) (Cronbach's alpha = 0.87) was tested at various levels through various means, including theme collection and reviews. The psychometric properties of the scale used by Braguglia (2008) have not been reported.

3.3.2.1.2.4. Nature of Adaptation

(i) CPU_Classroom (CPU_Switch)

For measuring the use of cell phones during class and/or study time, items were adapted from different scales and elaborated further as per the requirement of this study.

Bjornsen and Archer (2015) used four items to assess the use of cell phone in classroom. These items were followed by an instruction:

"Not including checking the time, how many times did you use your cell phone during this class to," followed by the CPUse items; (a) read or send email, text message, Facebook, Twitter (social media); (b) access Internet, a webpage, for something (information); (c) write myself a note, check my calendar (organization); (d) play a game (game).

The item used by Li et al. (2015) was "how many times do you check your mobile phone in a typical one-hour class period." Elder (2013) used six items to assess the frequency of CPU. The sample item was **"**I spend time texting when I should be doing homework/studying."

In this study, the item "how many times do you check your mobile phone in a typical one-hour class period" from Li et al. was elaborated to ten items in the lines similar as that of items used by Bjornsen and Archer (2015) and Elder (2013). Elaborated items assess the number of times a cell phone was used in class for various cell phone activities, such as texting, emailing, social networking, surfing the internet, checking reminders, and checking notifications.

All ten items were tied to a ratio-based scale (from 0 to 40) to capture precise responses on classroom CPU. The ratio-based scale will allow participants to indicate a number that is accurate for them. The list of classroom cell phone activities was extracted from previous studies (Li et al, 2015; Elder, 2013; Bjornsen & Archer, 2015; Berry & Westfall, 2015; Braguglia, 2008).

Items based on a particular cell phone activity (such as texting, emailing, social networking, and checking reminders) were further elaborated in the present study. For example, while previous studies just asked about a particular CPU, the present study asked about the "use of a cell phone for checking" and the "use of a cell phone for responding" separately. This particular modification was made to all CPU activities: texting, commercial/promotional, social media, emails, reminders, and surfing the internet. A total of nine items were finalized to measure the use of cell phones for self-regulated behaviors. A self-efficacy scale (Cronbach's alpha = 0.87) for self-regulated learning was used as a reference scale for all the items (Zimmerman, Bandura, and Martinez-Pons, 1992).

(ii) CPU_SRLBehavior

Items for measuring use of cell phones for self-regulated behaviors were adapted from existing studies. For example, items associated with smartphone self-efficacy and behavioral intentions to use smartphones ("a person's perceived likelihood that he or she will be engaged in a particular behavior") were derived from Han and Yi (2018). Items associated with self-regulated strategies involving the use of technology were adapted from the Self-regulated Learning with Technology at the University (SRLTU) scale developed by authors Yot-Domínguez and Marcelo (2017) (Cronbach's alpha = 0.87). An item assessing how often a cell phone can be used on a daily basis was adapted from a questionnaire developed by Braguglia (2008) and elaborated for other self-regulated behaviors along lines similar to that of the items used by Han and Yi (2018) and Yot-Domínguez and Marcelo (2017).

3.3.2.1.2.5. Experimenter-added Questions

(i) CPU_Classroom (CPU_Switch)

For the present study, two items were written by the researcher along lines similar to that of the original items to assess the use of cell phones to respond to commercial notifications. These items are as follows:

(i) During a 60-minute class, lab, and/or study session, how often do you check your cell phone for commercial notifications such as promotional offers (shopping, banking, etc.)?

0 times ……………………………...………….40 times

(ii) During a 60-minute class, lab, and/or study session, how often do you respond to commercial notifications such as promotional offers (shopping, banking, etc.) using your cell phone?

0 times ……………………………...………….40 times

(ii) CPU_SRLBehavior

No item was added by the experimenter in this construct.

3.3.2.1.3. CPU_SocialMedia

3.3.2.1.3.1. Number of items: 12

There are two sub-constructs of CPU_SocialMedia, which are as follows:

(i) CPU_SocialMediaFeelings

There are eight items in this construct to estimate how a cell phone makes participants feel from a social media standpoint (Instagram, Twitter, Facebook, Snapchat, LinkedIn, etc.) along different dimensions: engagement and connectedness, interest, pleasure, and sense of enjoyment, meaningfulness, purposefulness, optimism, belongingness and acceptance, and competence and feeling accomplished. These items will assess cell phone social media feelings on a Likert-based scale from ‘never’ to ‘always’ (1-“Never,” 2-"Occasionally," 3-"Often," and 4-“Always”). The average of the items provide a total score for CPU_SocialMediaFeelings. All items from CPU_SocialMediaFeelings hold good internal consistency (Cronbach alpha = 0.93).

(ii) CPU_SocialMediaResponses

There are four items in this construct to measure on a Likert-based scale from ‘never’ to ‘always’ (1-“Never,” 2-"Occasionally," 3-"Often," and 4-“Always”) how participants perceive a response to their own posts and their own responses to someone else's post on cell phone social media. These four items measure the feelings of connectedness, being liked by others, reward, and contributing to the well-being of others based on responses with social media apps (Instagram, Twitter, Facebook, Snapchat, LinkedIn, etc.). A response on social media included, but was not limited to, commenting, liking, sharing, loving, using emojis, posting GIF's, attaching stickers, etc. The average of the items provide a total score for CPU_SMResponses. All the items from CPU_SMResponses construct hold good internal consistency (Cronbach alpha = 0.93).

3.3.2.1.3.2. Item(s)/Instrument/Scale Used

Items for both CPU_SocialMedia sub-constructs, CPU_SocialMediaFeelings and CPU_SocialMediaResponses were adapted from common scales/instruments used in previous studies.

Scales used: Social Media Use Integration Scale (Jenkins-Guarnieri, Wright, & Brian Johnson, 2013), Social Media Addiction Scale (Sahin, 2018), SMengage-Basic-Scale (Hou, 2017), Mobile Phone Use Scale (Chan, 2013), Emotion Regulation Questionnaire (Hoffner & Lee, 2015), items for friending on cell phone social media, self-disclosure on cell phone social media, and bridging and bonding on cell phone social media (Chen and Li, 2017).

3.3.2.1.3.3. Reliability and Validity Evidence

The evidence of reliability and validity of items from both CPU_SocialMediaFeelings and CPU_SocialMediaResponses sub-constructs will be presented together, as the items in both the sub-constructs were adapted from common scales/instruments validated in previous studies.

The Social Media Use Integration Scale, developed by Jenkins-Guarnieri, Wright, and Brian Johnson (2013), has gone through several validity checks, such as item pool (pooling items), expert opinion, revision, and removal of irrelevant and redundant items. The scale was further tested for convergent, discriminant, and concurrent validity, and was found to be valid on all validity psychometrics. This scale was also found to be reliable as the items in the scale possessed good internal consistency (Cronbach alpha for the total scale was 0.91 and Cronbach alpha for sub-scales 1 and 2 were 0.89 and 0.83). The psychometric properties of this scale were tested on social media platforms Facebook and LinkedIn using samples from African contexts by Maree in 2017; the scale was found to be reliable (Cronbach alpha = 0.89) and valid.

The Social Media Addiction Scale developed by Sahin (2018) was based on a strong conceptual framework addressing social media use and addiction. The content validity of the scale was tested using standard measures, such as expert reviews and I-CVI measurement (item-level content validity index). Construct validity of the scale was examined using exploratory and confirmatory factor analysis. Internal consistency and stability analysis were also conducted. Items from various constructs of the scale possessed good internal consistency (Cronbach alpha for various constructs of the scale varies from 0.81 to 0.86) and the overall scale produced stable measurements (Sahin, 2018).

The SMengage-Basic-Scale developed by Hou (2017) was reviewed at various levels at the construction phase, tested for criterion and discriminant validity, and was valid on all grounds. Items from this scale were also held good internal consistency (Cronbach alpha = 0.87). All the items adapted from suitable constructs, such as friending on cell phone social media (Spearman-Brown coefficient = 0.78), self-disclosure on cell phone social media (Cronbach alpha = 0.91), and bridging and bonding on cell phone social media (Cronbach alpha for various constructs of the scale varies from 0.74 to 0.81) of a study conducted by Chen and Li (2017) were valid. The items used by Chen and Li were adapted from existing scales used in the previous studies (Chen & Chen, 2015; Williams, 2006), where all the scales/items were tested and verified for their reliability and validity.

To address validity issues in the Mobile Phone Use Scale, Chan (2013) identified three focus groups from different CPUser demographics and developed a list of cell phone features. Based on the feedback, Chan has created 12 questions. These items were evaluated for psychometric properties and were found to possess good internal consistency (Cronbach alpha = 0.87). The Emotion Regulation Questionnaire was a reliable and valid measure of emotion regulation as Hoffner and Lee have created this questionnaire using feedback data from participants on a five day long hypothetical cell phone loss scenario. Principal factor analysis and item analysis were conducted for the questionnaire, and the items from all three constructs were found to hold good internal consistency (Cronbach alpha for the constructs varies from 0.79 to 0.91).

3.3.2.1.3.4. Nature of Adaptation

Majority of items of CPU_SocialMediaFeelings and CPU_SocialMediaResponses sub-constructs were adapted from the Social Media Use Integration Scale (Jenkins-Guarnieri, Wright, & Brian Johnson, 2013) and Social Media Addiction Scale (Sahin, 2018). Items based on reading, and responding to, social media posts were adapted from a SMengage-Basic-Scale developed by Hou (2017). Items were also adapted from suitable constructs, such as friending on cell phone social media, self-disclosure on cell phone social media, and bridging and bonding on cell phone social media of a study conducted by Chen and Li (2017). Items were also adapted from the mobile phone communication construct of the Mobile Phone Use Scale developed by Chan (2013). Besides, items from all three sections of the construct “Missed uses/functions of mobile phone if lost” of Emotion Regulation Questionnaire developed by authors Hoffner and Lee (2015) were adapted for measuring use of cell phones for social media in the present study.

3.3.2.1.3.5. Experimenter-added Questions

No item was added by the experimenter in the CPU_SocialMediaFeelings and CPU_SocialMediaResponses sub-constructs.

3.3.2.1.4. CPU_Total

3.3.2.1.4.1. Number of items: 10

There are no sub-constructs of CPU_Total. The items from this construct estimate the total amount of time spent using cell phone per day on a scale from 0 to 12 hrs. for calling, texting, taking photos or recording videos, listening to Podcasts, watching videos (Netflix, Hulu, etc.), gaming, non social media internet browsing (Shopping, surfing, etc.), social media (Instagram, Twitter, Snapchat, Facebook, etc.) email (sending and receiving), and other app or software driven use not listed above. Total score range from 0 to 24 hrs., the maximum number of hours in a day and night cycle.

3.3.2.1.4.2. Instrument/Scale Used

Total CPU item from Lepp et al. (2013; 2014; 2015).

3.3.2.1.4.3. Reliability and Validity Evidence

The content validity of the total daily CPU items was tested by Lepp et al. (2015) using students' feedback on various aspects including clarity of words, relevance, linguistic appropriateness, clarity of instruction, and formatting. Construct and criterion validity of the items were assessed using the total daily CPU data from self-reported measures and from actual cell phone records of a small sample (n = 21) of college students. These items were found to be valid on all psychometric standards.

3.3.2.1.4.4. Nature of Adaptation

To make a precise estimate of the total amount of time spent on a cell phone per day, various CPU items were adapted from existing scales used in previous studies. A total CPU item from Lepp et al. (2013; 2014; 2015) was used as a base question, in which two CPU operations/activities (listening to Podcasts and listening to music) were included. The total daily CPU question from Lepp et al. is as follows: ‘‘As accurately as possible, please estimate the total amount of time you spend using your mobile phone each day. Please consider all uses except listening to music. For example, consider calling, texting, Facebook, e-mail, sending photos, gaming, surfing the Internet, watching videos, and all other uses driven by ‘apps’ and software.’’ Lepp et al. (2015) have estimated the total time in hours and minutes per day, and then converted them into total number of minutes, however, Li et al. (2015) have asked participants “to fill in a blank for hours of cell phone per day and minutes per day (Total Minutes Per Day = Hours ⁄ 60 + Minutes).”

In the present study, a bar scale ranging from 0 to 12 hrs. was used and the cell phone operations/activities included are calling, texting, taking photos or recording videos, listening to Podcasts, gaming, browsing the Internet (shopping, surfing, scrolling, etc.), watching videos (Netflix, Hulu, etc.), using social media (Instagram, Twitter, Snapchat, Facebook, LinkedIn, etc), sending and receiving emails, and using other apps or software-driven uses not listed here.

The CPU activities/operations in a few items of Lepp et al. (2013; 2014; 2015) were modified as per the requirement of the present study. The ‘sending photos’ item was modified to ‘taking photos or recording videos,’ ‘watching videos’ item was modified to ‘watching videos (Netflix, Hulu, etc.),’ ‘surfing the Internet’ item was modified to ‘browsing the Internet (shopping, surfing, scrolling, etc.),’ ‘Facebook’ item was modified to social media (Instagram, Twitter, Snapchat, Facebook, LinkedIn, etc),’ and ‘e-mail’ item was modified to ‘sending and receiving emails.’

3.3.2.1.4.5. Experimenter-added Questions

For the present study, one item was written by the researcher along lines similar to that of the original items to assess the total amount of time spent per day listening to Podcasts. The item is as follows:

(i) As accurately as possible, please estimate the total amount of time you spend using your cell phone per day on each of the following uses

Listening to Podcasts	0 to 12 hrs.

3.4. Procedures

Data will be collected through an online quantitative survey, which will be designed using psychometric principles aligned with best practices for constructing an online assessment tool. The quantitative survey design is intended to help collect data on demographic information of undergraduate students that includes their sex, ethnicity, age, years of attending college, and declared major. The respondent-friendly design criteria ("Principles for Constructing Web Surveys," n.d.) of the web questionnaires will be followed. Likert scale and single-click radio button-based questions will also be given due consideration. The survey will avoid using open-ended questions and sub-questions. The survey will exclude mixed-mode methods (survey and telephonic interview) and the graphical symbols that need advanced programming. A survey progression (timer) will also be included in the survey to keep the respondents engaged. The survey will be designed in only black and white so that it would be clearly readable and easy to navigate. Elements of frustration, such as drop-down boxes, open-ended questions, and unclear skip lines will be avoided. The survey will be compatible with mobile devices as it is presumed students with high cell phone use would prefer this interface method.

Before administering the main study, pilot studies will be conducted to gauge various factors including the time required for completion of the survey. Reliability will be tested further using the data from the main study. The next procedural step involves survey administration, which is the key for ensuring the reliability of the data collected during the study. A consistent measurement procedure will be followed in which the same set of questions will be distributed, using identical methods, to all the participants. The self-reported online survey will be distributed to un-identified samples from a diverse population, which will provide a rich data source for the study. Qualified participants will be able to complete the study survey within 20 – 30 minutes anytime in the study period from anywhere on their personal devices. A follow-up measure of redistributing the email invitations will be taken two to three times to increase response rate and sample size.

Qualified participants will be asked to provide demographic information to ensure that the participants from the target population are represented in the sample. The scales will be arranged in the instrument in order of demographic information, academic performance (GPA), CPU scale, PWB scale, and PSQI. The psychometric properties of the instrument will be determined in collaboration with committee members. All the suggested changes that ensured the validity will be applied in the instrument. In addition to these measures, a team of researchers will take the survey before sending it out to ensure that the questions are clear and the overall design was in working order. The survey responses will be downloaded into a data management file and will be used for further investigation. Once the data collection process is over, the data would be transferred from Qualtrics survey to a Microsoft Excel spreadsheet. The data in the Excel sheet would be cleaned before importing into the data analysis tool, SPSS.

3.5. Data analysis plan

3.5.1. Descriptive Analyses

Descriptive analyses will be used to examine the characteristics of the sample and the characteristics of the study variables. Demographic data will be analyzed in terms of gender, ethnicity, number of years in college, and colleges and majors. The descriptives of continuous variables such as age, CPU_Total, CPU_BeforeBed, CPU_Arousal, CPU_Switch, CPU_SRL, CPU_SMF, CPU_SMR, GPA, and PWB will be analyzed in terms of the measures of central tendency including mean, median, mode, standard deviation, and skewness. The descriptives of categorical variables such as sleep latency and sleep difficulty will be analyzed in terms of frequency, percent, and cumulative percent.

Before descriptive analysis, factor analysis will be performed in order to determine the alignment and interrelationships among the items of the scales, which will help establish the construct validity of the scales. The factor analysis will serve two primary purposes here: determining common factors and determining the relationship between factors and the test items. Analysis of variance (ANOVA; a one – way) will be used for analyzing variances among variables. Cronbach's alpha will be used to measure internal consistency (scale reliability) within the items in the scales. The significance level for all the analyses will be set as 0.05, which means that the probability of Type I error would be maintained at 0.05.

3.5.2. Inferential analyses

Inferential analyses will be used to present the outcomes of hypotheses testing from the domains of sleep quality, academic performance, and PWB of undergraduate students. A control analysis will be administered for all the independent and dependent variables prior to conducting correlation and regression. The control analysis will inform about the qualification of each study variable for a particular correlation and regression analysis. The correlational quantitative research will attempt to determine the extent of relationships. This methodology will also allow examining the relationships between the dependent variables in order to recognize trends and patterns. Consequently, this study is not intended to establish a cause and effect. In addition, only the relationships between the variables will be observed because correlational research does not allow manipulating variables. Rather, the variables will be identified and analyzed as they occur from the natural setting.

The correlation coefficients (Spearman rank-order correlation coefficient) will be used to measure the relationship between independent and dependent variables from the domains of sleep quality, academic performance, and PWB. The linear regression and logistic regression will be used to predict the impact of independent variables on the outcome variables. The partial eta squared will be used to determine the effect size between the groups. Overarching themes and findings will be presented in the result section along with the hypothesized explanations as to why the results turned out the way they did. The result section will also present a detailed explanation of the reasons for why and how various hypotheses in the study were either accepted or rejected. Limitations of the study will be discussed at the end of the study, which will likely lead to future research possibilities.

4. RESULTS

4.1. Descriptive Analyses

4.1.1. The Characteristics of the Sample

A total of 718 undergraduate students took the survey from which 193 responses were found incomplete. The sample consisted of 525 undergraduate students between 18 and 50 years old, with an average age of 20.19 years (SD = 3.18); 98.9% of the participants were between the age of 18 and 30. From this sample, 75.4% of the participants were female, 24.2% male, and 0.4% of the participants preferred not to answer. A demographic comparison of the CPU study sample with the current Texas A&M undergraduate population as a whole is presented in Table 1. As shown in Table 1, 95% confidence level margin of error for the CPU study sample was ± 4.25%. This means that the CPU study statistics are expected to differ 4.25% points from the Texas A&M population parameters ("Margin of error calculator," n.d.).

Clarifying further, if the CPU study survey had been completed by the entire Texas A&M population, 95% of the time, 45836 (95.75%) of the undergraduate students would have picked the same answers that were picked by the CPU study sample. In other words, if the CPU study survey is repeated using the same methods, 95% of the time the CPU study sample statistics will represent the Texas A&M population parameters with ± 4.25% margin of error. It is noteworthy to mention that, in survey-based studies, with random sampling, a margin of error of up to ± 8% (95% confidence level) is acceptable (Dillman, Smyth, & Christian, 2014). In the case of CPU study, 95% of the time the CPU study sample statistics would have represented Texas A&M population parameters if the sample size had been between 483 and 567 (525 ± 8%).

Table 4.1

Texas A&M Most Recent Demographic Data, Representative Sample, and the Cell Phone Use Study Sample Characteristics

		Cell Phone Use Study Sample		Texas A&M Spring 2020 Headcount*	
		Frequency	Percent	Frequency	Percent
Sex					
	Male	127	24.2	25563	53.4
	Female	396	75.4	22307	46.6
Ethnicity					
	Caucasian	241	45.9	28052	58.6
	Latinx	133	25.3	11872	24.8
	Asian	107	20.4	4117	8.6
	African American	17	3.2	1532	3.2
	Others	19	3.6	1436	3.0
Colleges					
	College of Engineering	151	28.8	14600	30.5
	College of Agriculture and Life Sciences	90	17.1	5888	12.3
	College of Liberal Arts	82	15.6	7262	15.2
	College of Science	46	8.8	2307	4.8
	College of Education and Human Development	45	8.6	4687	9.8
	Mays Business School	39	7.4	4639	6.7
	College of Veterinary Medicine and Biomedical Sciences	37	7	2513	5.3
	Total Participants/Headcounts	525		47870	
	Margin of Error (95% Confidence Level)		± 4.25	± 2034	

Note. *Data from the most recent census at Texas A&M ("Student data and reports," n.d.).

4.1.2. The Descriptive Analyses of Continuous Variables

In the sample of 525 undergraduate students, with no missing data and an average age of 20.19 years, most of them were 18 years of age (Mode = 18) (Table 2) (see Appendix G, for missing data case processing summary). Undergraduate students spent an average time of 9.68 hours per day (SD = 7.99) engaging in various cell phone activities (see Appendix I, for detailed test-statistics). Latinx undergraduate students (11.69 ± 9.68), as compared to Caucasian undergraduate students (9.06 ± 7.59), were found to have slightly higher CPU_Total as determined by the effect size. Further, Latinx undergraduate students were engaged more, as compared to Asian and Caucasian undergraduate students, in watching videos, with medium effect size, and on social media, with small effect size, using their cell phones. There were no statistically significant differences found on the measure of per-day CPU between sex, year in college, and college type as determined by a one-way ANOVA (Appendix I).

Table 4.2

The Descriptive Statistics of Continuous Variables Age, CPU_Total, CPU_BeforeBed, CPU_Arousal, CPU_Switch, CPU_SRL, CPU_SMF, CPU_SMR, GPA, and PWB (N = 525)

	Minimum	Maximum	Mean ± SD	Mode	Skewness
Age	18	50	20.19 ± 3.18	18.00	4.37
CPU_Total	0.00	92.00	9.68 ± 7.99	7.50	4.66
CPU_BeforeBed	9	36	17.69 ± 4.32	17.00	0.78
CPU_Arousal	6	54	16.03 ± 8.38	6.00	1.26
CPU_Switch	0.00	40.0	3.52 ± 4.18	1.10	3.67
CPU_SRL	1.33	4.00	2.84 ± 0.56	3.00	0.06
CPU_SMF	1.00	4.00	2.09 ± 0.65	2.00	0.64
CPU_SMR	1.00	4.00	2.42 ± 0.80	2.00	0.15
GPA	1.63	4.00	3.32 ± 0.47	4.00	-0.55
PWB	8	40	31.62 ± 5.54	32.00	-0.83

Note. CPU_Total = Total hours-per-day spent using cell phones, CPU_BeforeBed = The use of cell phone before sleep, CPU_Arousal = The use of cell phones for accessing sexually explicit, violently, or emotionally charged media content, CPU_Switch = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRL = The use of cell phones for self-regulated learning strategies, CPU_SMF = The use of cell phones for social media feeling, CPU_SMR = The use of cell phones for social media response, GPA = Grade Point Average, PWB = Psychological Well-Being.

The CPU_BeforeBed of undergraduate students varied from 9 to 36 on a scale of 1 to 4, with an average of 17.69 (SD = 4.32). Computing the mean scores of CPU_BeforeBed (16.73 – 18.77) on demographic variables showed that undergraduate students occasionally (infrequently but not compulsively) used cell phones before bed. There was a statistically significant ($p < 0.01$) effect of variable sex ($F(2, 522) = 4.514$, $p < 0.01$, eta squared = 0.02) and college ($F(16, 508) = 2.030$, $p < 0.01$, eta squared = 0.06) on the CPU_BeforeBed of undergraduate students, as determined by a one-way ANOVA (see Appendix I, for detailed test-statistics). Female undergraduate students (17.97 ± 4.32), as compared to male undergraduate students (16.89 ± 4.21) had a slightly higher CPU_BeforeBed as determined by the effect size. There was no difference ($p < 0.01$) among variable college, as determined by post-hoc analyses. The item-level CPU_BeforeBed score of undergraduate students revealed that female undergraduate students (2.79 ± 0.89) stayed up late more often to use social media on their cell phones as compared to male undergraduate students (2.50 ± 0.91). The item-level CPU_BeforeBed score also revealed that female undergraduate students (2.76 ± 0.89) stayed up later to watch videos on their cell phones compared to male undergraduate students (2.52 ± 0.87) (Appendix I).

The CPU_Arousal varied from 4 to 54 on a scale of 1 to 10, with an average of 16.03 (SD = 8.38). It was moderately common (score; 14.30 – 19.31) that undergraduate students had mental (cognitive), emotional or psychological arousal due to the use of cell phones on a scale ranging from 1 to 10 (1-“not common at all” and 10-“extremely common”). There was a small, but statistically significant ($p < 0.001$) effect of variable sex ($F(2, 522) = 13.468$, $p < 0.001$, eta squared = 0.05) on the CPU_Arousal of undergraduate students, as determined by a one-way ANOVA (see Appendix I, for detailed test-statistics). Male undergraduate students (19.31 ± 10.16), as compared to female undergraduate students, (14.99 ± 7.46) had higher CPU_Arousal.

The item-level CPU_Arousal score of undergraduate students revealed that male undergraduate students (3.71 ± 2.68) were engaged more often in explicit content pertaining to sexuality using their cell phones as compared to female undergraduate students (1.85 ± 1.72). Moreover, male undergraduate students (2.50 ± 2.23) stayed awake longer to engage in sexually-oriented cell phone apps than female undergraduate students (1.54 ± 1.32). The item-level CPU_Arousal score also revealed that male undergraduate students (3.39 ± 2.65) were engaged more in explicit content pertaining to violence as compared to female undergraduate students (1.94 ± 1.80). Also, male undergraduate students (2.28 ± 2.04) stayed awake longer to engage in violence-based cell phone apps than female undergraduate students (1.46 ± 1.29) (Appendix I).

The mean scores of CPU_Switch of undergraduate students in terms of demographic variables sex, ethnicity, year in college, and college showed that the average frequency in all groups ranged from 2.57 – 4.43, with an average of 3.52 (SD = 4.18), on a scale of 0 to 40. This range of frequency indicated that undergraduate students switched to their cell phones three to four times during a 60-minute class/lecture, lab, and/or study session for various reasons. There were no statistically significant ($p < 0.01$) difference between the group means of variables sex, ethnicity, year in college, and college for CPU_Switch, as determined by a one-way ANOVA (Appendix I).

Undergraduate students "often" (score; 2.73 – 3.04 on a scale ranging from 1 to 4 (1-"Never," 2-"Occasionally," 3-"Often," and 4-"Always")) used cell phones for self-regulated behaviors. The variable sex had a statistically significant ($p < 0.01$) effect on the CPU_SRL of undergraduate students ($F(2, 522) = 4.588$, $p < 0.01$, eta squared = 0.02), as determined by a one-way ANOVA. The CPU_SRL of female undergraduate students (2.88 ± 0.53) was higher than that of male undergraduate students (2.73 ± 0.62). The variable sex had an impact, with a small effect size on undergraduate students' use of cell phones for self-regulated strategies, such as alarm, timer/stop watch/clock, and email and social media. Female undergraduate students, as compared to male undergraduate students had higher mean scores for all CPU_SRL strategies listed (Appendix I).

The variable ethnicity also had a statistically significant ($p < 0.01$) effect on the CPU_SRL of undergraduate students ($F(6, 518) = 4.102$, $p < 0.001$, eta squared = 0.05), as determined by a one-way ANOVA. Asian undergraduate students (3.04 ± 0.55), as compared to Caucasian (2.81 ± 0.55) and Latinx (2.80 ± 0.55) undergraduate students had higher CPU_SRL. The variable ethnicity had an impact, with small effect size on undergraduate students' use of cell phones for self-regulated strategies, such as calendar, notes, Google docs, email and social media, and texts. Asian undergraduate students, as compared to Latinx and Caucasian undergraduate students had higher mean scores for all mentioned CPU_SRL strategies (Appendix I).

Undergraduate students "occasionally" (score; 1.99 – 2.36 on a scale ranging from 1 to 4 (1-"Never," 2-"Occasionally," 3-"Often," and 4-"Always")) related the use of their cell phones for social media with their feelings. There was a statistically significant ($p < 0.01$) difference between the group means of variable ethnicity ($F(6, 518) = 4.935$, $p < 0.01$, eta squared = 0.05) for CPU_SMF, as determined by a one-way ANOVA (see Appendix I, for detailed test-statistics). Asian undergraduate students (2.36 ± 0.76), as compared to Caucasian undergraduate students (1.99 ± 0.59) had higher CPU_SMF. The variable ethnicity had a statistically significant ($p < 0.01$) effect**,** with small and medium effect sizes on CPU_SMF activities: engaged and connected, interested, enjoyment, meaningfulness, purposefulness, optimism, belongingness and acceptance, and competence and accomplishment (see Appendix I, for more details). Asian undergraduate students, as compared to Caucasian undergraduate students had higher CPU_SMF scores for all activities mentioned.

The CPU_SMR mean scores of undergraduate students on demographic variables sex, ethnicity, year in college, and college varied between "occasionally" and "often" (score; 2.24 – 2.54 on a scale ranging from 1 to 4 (1-"Never," 2-"Occasionally," 3-"Often," and 4-"Always")). Undergraduate students were able to relate to their cell phone social media responses but on a varied scale. The variables sex, ethnicity, year in college, and college had no statistically significant ($p < 0.01$) effect on the CPU_SMR of undergraduate students, as determined by a one-way ANOVA (see Appendix I, for detailed test-statistics).

4.1.3. The Descriptive Analyses of Categorical Variables

4.1.3.1. The Descriptive Statistics of Sleep Latency

The sleep latency of undergraduate students was measured in terms of two parameters: time taken to fall asleep each night after going to bed and the frequency of trouble sleeping on a weekly basis for the past month. The participants were assigned scores ranging from 0 to 3 based on the time taken to fall asleep each night after going to bed during the past month (0-“15 minutes or less,” 1-“16 - 30 minutes,” 2-“31-60 minutes,” and 3-“more than 60 minutes”). The frequency of not being able to get to sleep within 30 minutes after going to bed was also rated in terms of scores ranging from 0 to 3 (0-“not during the past month,” 1-“less than once a week,” 2-“once or twice a week,” and 3-”three or more times a week”). As per the scoring instructions of the Pittsburgh Sleep Quality Index, both the scores were added to get the composite score (Buysse et al., 1989), and the composite score was used to determine the sleep latency of undergraduate students during the past month.

Table 4.3

The Descriptives of Categorical Variables: Sleep Latency and Sleep Difficulty (N = 525)

Sleep Latency				Sleep Difficulty			
Scores	Frequency	Percent	Cumulative Percent	Scores	Frequency	Percent	Cumulative Percent
0	141	26.9	26.9	0	28	5.3	5.3
1	195	37.1	64.0	1	379	72.2	77.5
2	122	23.2	87.2	2	111	21.1	98.7
3	67	12.8	100.0	3	7	1.3	100.0
Total	525	100.0			525	100.0	

As Table 3 shows, one quarter (26.9%) of undergraduate students reported having no sleep latency as they were able to fall asleep each night within or less than 15 minutes after going to bed. The remaining three quarters (73.1%) of undergraduate students reported low, moderate, or high sleep latency, with some sort of trouble sleeping during the past month. Of these students, 37.1% of undergraduate students reported low sleep latency as they could not get to sleep within 30 minutes, 23.2% reported moderate sleep latency as they could not get to sleep within 60 minutes, and 12.8% of undergraduate students reported high sleep latency as it takes more than 60 minutes to fall asleep. The low, moderate, and high intensity of sleep latency were also determined by the frequency of days with trouble sleeping, ranging from less than once a week, once or twice a week, and three or more times a week that undergraduate students weren't able to get to sleep within 30 minutes. There were no statistically significant ($p < 0.01$) differences found on the measure of sleep latency between Sex, Ethnicity, year in College, and college type as determines by a Kruskal-Wallis test.

4.1.3.2. The Descriptive Statistics of Sleep Difficulty

The sleep difficulty was assessed by the frequency of trouble undergraduate students had sleeping during the past month due to various reasons including waking up in the middle of the night or early morning, getting up to use the bathroom, uncomfortable breathing, coughing or snoring loudly, feeling too cold, feeling too hot, etc. (Buysse et al., 1989). The participants chose from sleep difficulty scores ranging from 0 to 3 (0 - "not during the past month", 1 - "less than once a week", 2 - "once or twice a week" and 3 - three or more times a week). From the study sample, 94.7% of undergraduate students reported having trouble sleeping (Table 3). Of that sample, 72.2% of them had trouble sleeping for less than once a week, 21.1% had it once or twice a week, and 1.3% had trouble sleeping for three or more times a week. However, 5.3% of undergraduate students reported no sleep difficulty. There were, however, no statistically significant ($p < 0.01$) differences found on the measure of sleep difficulty between sex, ethnicity, year in college, and college type as determines by a Kruskal-Wallis test.

4.2. Inferential Analyses

This section will present the outcomes of hypotheses testing from the domains of sleep quality, academic performance, and PWB of undergraduate students. A control analysis was administered for all the independent and dependent variables prior to conducting correlation and regression. The sleep quality variables, i.e., sleep latency and sleep difficulty (categorical, ordinal scale based, non-dichotomous data) qualified for logistic regression. Both the variables, GPA (continuous, non-normal, skewed, interval scale based, homoscedastic data) and PWB (continuous, non-normal, skewed, ordinal scale based, heteroscedastic data), qualified for Spearman rank-order correlation. Furthermore, the variables GPA and PWB qualified for linear regression and logistic regression respectively (see Appendix F and H, for more detail).

4.2.1. Hypotheses from the Domain of Sleep Quality

H1a: *We expect, according to sleep displacement theory, the CPU for* *unstructured leisure activities before sleep to relate positively to the sleep latency of undergraduate students.*

H1a was supported.

An ordinal logistic regression (Table 4) was conducted to analyze the correlation between CPU variables (CPU_BeforeBed and CPU_Arousal) and sleep quality variables. The crude odds ratio shows that there are higher odds of sleep latency occurring with the exposure to the use of cell phones for unstructured leisure activities before sleep (CPU_BeforeBed) [Exp (B) = 1.091, $p < 0.001$]. The likelihood chi-square ratio showed that CPU_BeforeBed had a statistically significant correlation with sleep quality [chi-square (1) = 6.839, $p < 0.01$]. The model was tested for proportional odds ratios prior to conducting ordinal logistic regression, and the assumption of proportional odds was found to be satisfied (as $p = 0.682$), which means that CPU_BeforeBed parameters were not the same across sleep latency categories. The model chosen to predict the sleep quality improved our ability to predict the correlation between CPU_BeforeBed and sleep latency as the model significantly fits the null model [Omnibus test chi-square (12) = 22.519, $p < 0.01$]. The adjusting crude odds ratio, however, reduced the ability to predict the effect of CPU_BeforeBed on the sleep latency of undergraduate students after controlling variables, such as sex, ethnicity, college, age, years in college, CPU_Total, CPU_Arousal, CPU_Switch, CPU_SRLBehavior, CPU_SMFeeling, and CPU_SMResponse. Nevertheless, CPU_BeforeBed significantly predicted the sleep latency of undergraduate students [Exp

(B) = 1.063, $p < 0.01$]. Combining correlational and descriptive statistics together, undergraduate students occasionally used their cell phones before bed, which, therefore, increased their sleep latency.

Table 4.4

Ordinal Logistic Regression Analyses Showing Correlation Between CPU Variables (CPU_BeforeBed and Sleep Latency) and Sleep Variables (Sleep Latency and sleep difficulty) (N = 525)

Dependent Variable	Independent Variable	Odds Ratio	
		Crude OR (95% CI)	Adjusted OR (95% CI)[a]
Sleep latency	CPU_BeforeBed	1.091 (1.015 - 1.112)**	1.063 (1.050 - 1.134)*
Sleep Difficulty	CPU_Arousal	1.065 (1.042 - 1.089)**	1.064 (1.035 - 1.094)**

Note. CPU_Total = Total hours-per-day spent using cell phones, CPU_BeforeBed = The use of cell phone before sleep, CPU_Arousal = The use of cell phones for accessing sexually explicit, violently, or emotionally charged media content, CPU_Switch = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRL = The use of cell phones for self-regulated learning strategies, CPU_SMF = Cell phone social media feeling, CPU_SMR = Cell phone social media response.

[a] adjusted for sex, ethnicity, colleges, age, years in college, CPU_Total, CPU_BeforeBed, CPU_Arousal, CPU_Switch, CPU_SRL, CPU_SMF, and CPU_SMR.

*$p < 0.01$; **$p < 0.001$.

H1b: *We expect, according to arousal theory (media content), CPU for accessing Sexually explicit, violently, or emotionally charged media content before sleep to relate positively to the sleep difficulty (sleep disturbance) of undergraduate students.*

H1b was supported.

The crude odds ratio showed that there were higher odds of sleep difficulty occurring when cell phones were used for accessing sexually explicit, violently, or emotionally charged media content before sleep (CPU_Arousal) [Exp (B) = 1.065, $p < 0.001$] (Table 4). The likelihood*/ chi-square ratio also showed that the CPU_Arousal of undergraduate students was significantly correlated with their sleep difficulty [chi-square (1) = 19.785, $p < 0.001$]. The CPU_Arousal parameters fit well in the proportional odds ratio assumption of independence across all of the sleep difficulty categories within the model (as $p = 0.927$) chosen to predict the sleep difficulty of undergraduate students. Controlling the variables such as sex, ethnicity, college, age, years in college, CPU_Total, CPU_BeforeBed, CPU_Switch, CPU_SRLBehavior, CPU_SMFeeling, and CPU_SMResponse had a minimal impact on the ability of the model to predict the effect of CPU_Arousal on the sleep difficulty of undergraduate students. However, the model improved the ability to predict the correlation between CPU_Arousal and sleep difficulty [Omnibus test chi-square (12) = 60.694, $p < 0.001$], and the CPU_Arousal significantly predicted the sleep difficulty of undergraduate students [Exp (B) = 1.064, $p < 0.001$]. Putting correlational and descriptive statistics together, it was moderately common for undergraduate students to engage in CPU_Arousal activities before bed, which, therefore, increased their sleep difficulty.

4.2.2. Hypotheses from the Domain of Academic performance

H2a: *We expect, according to the switch-load theory, the frequency of cell phone Checking during a class/lecture, lab and/or study session to negatively relate to the academic performance (GPA) of undergraduate students.*

H2a was supported.

Spearman rank-order correlation was conducted to assess the correlation of GPA and PWB with their respective predicting variables (Table 5). A hierarchical regression (Table 6) was administered to see how the CPU variables of academic performance (CPU_Switch and CPU_SRLBehavior) predicted the GPA of undergraduate students. As Table 15 shows, the frequency of CPU during a class/lecture, lab and/or study session (CPU_Switch) was negatively correlated to the GPA of undergraduate students. This correlation was weak; however, it was statistically significant ($p < 0.05$).

Table 4.5

Nonparametric Correlations (N = 525)

		CPU_Switch	CPU_SRL	CPU_SMF	CPU_SMR	GPA	PWB
Spearman's rho	CPU_Switch	1.000					
	CPU_SRL	.309**	1.000				
	CPU_SMF	.256**	.242**	1.00			
	CPU_SMR	.231**	.242**	.657**	1.000		
	GPA	-.094*	0.002	-0.07	-0.031	1.000	
	PWB	-0.013	.192**	.172**	.126**	0.058	1.000

Note. CPU_Switch = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRL = The use of cell phones for self-regulated learning strategies, CPU_SMF = Cell phone social media feeling, CPU_SMR = Cell phone social media response, GPA = Grade point average, PWB = Psychological well-being.

*p < 0.05 (2–tailed); **p < 0.01 (2–tailed).

Hierarchical regression showed that the ANOVA results of the model were statistically significant (R^2 = .02, F (12, 511) = 1.92, $p < 0.05$), which means that the model can explain the variability of the data within the data set. The beta coefficient of CPU_Switch (*Beta* = -0.05) was not statistically significant (Table 6), which means CPU_Switch was not a significant predictor of the academic performance of undergraduate students. Combining correlation and regression outcomes together, the increase in CPU_Switch may be one of the factors for a decreased GPA of undergraduate students, but the increased CPU_Switch can not be used as a predictor for a change in the GPA. Hierarchical regression also showed that the controlling variables total CPU (beta = -0.09) and CPU arousal (beta = -0.11) predicted the GPA of undergraduate students. Bringing all results together, undergraduate students switched to their cell phones during a class/lecture, lab, and/or study session, which negatively affected their academic performance.

Table 4.6

Hierarchical Regression of Demographics and Cell Phone Use Variables on Grade Point Average

	Variables	Grade Point Average *(Beta Coefficients)*
Demographic information		
	Sex	-0.01
	Age	0.01
	Ethnicity	-0.12*
	Colleges	-0.01
	Years in college	0.04
Cell phone use variables		
	CPU_Total	-0.09*
	CPU_BeforeBed	0.01
	CPU_Arousal	-0.11*
	CPU_Switch	-0.05
	CPU_SRL	0.02
	CPU_SMF	-0.04
	CPU_SMR	0.02
	Adjusted R^2	0.02
	N	524

Note. All betas are standardized coefficients. CPU_Total = Total hours-per-day spent using cell phones, CPU_BeforeBed = The use of cell phone before sleep, CPU_Arousal = The use of cell phones for accessing sexually explicit, violently, or emotionally charged media content, CPU_Switch = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRL = The use of cell phones for self-regulated learning strategies, CPU_SMF = Cell phone social media feeling, CPU_SMR = Cell phone social media response.

*$p < 0.05$.

H2b: *We expect, according to Zimmerman's theory of self-regulated learning (SRL), The use of cell phones for self-regulated learning strategies (metacognitive, motivational, and behavioral) to relate positively to the academic performance (i.e., college GPA) of undergraduate students.*

H2b was not supported.

The Spearman rank-order coefficient for the use of cell phones for self-regulated learning strategies (CPU_SRLBehavior) was not statistically significant (0.002, p = 0.961) (Table 5). This result indicated that CPU_SRLBehavior was unrelated to the academic performance (GPA) of undergraduate students. More specifically, the use of cell phones for self-regulated learning strategies, such as using an alarm, calendar, calculator, notes, Google Docs, timer, emails, and texts did not have an impact on undergraduate students' academic performance. Although, CPU_Switch was found to be correlated with CPU_SRLBehavior of undergraduate students (0.309, $p < 0.001$), which could help fix issues concerning CPU_Switch during a class/lecture, lab and/or study session. The measures concerning CPU_SRLBehavior, whether in terms of GPA or CPU_Switch, may have potential benefits for young adult CPU but warrant further research in these areas. Combining correlational and demographic test-statistics, undergraduate students often used cell phones for self-regulated activities, specifically alarm, timer/stopwatch/clock, notes, Google docs, texts, and email and social media. However, CPU_SRL strategies did not affect their academic performance.

4.2.3. Hypotheses from the Domain of Psychological Well-Being

H3a: *We expect, according to humanistic theories of positive functioning, cell phone Social media feeling to relate positively (due to anytime-anywhere accessibility of cell phones) to the PWB of undergraduate students.*

H3a was supported.

The cell phone social media feeling (CPU_SMFeeling) was positively correlated with the PWB of undergraduate students (Spearman's coefficient = 0.172, $p < 0.001$) (Table 5). The crude odds ratio also indicated that there are higher odds of PWB happening with CPU_SMFeeling of undergraduate students [Exp (B) = 1.798, $p < 0.001$] (Table 7). Further, the correlation between CPU_SMFeeling and PWB was confirmed by the likelihood chi-square ratio [chi square (1) = 15.129, $p < 0.001$]. The CPU_SMFeeling parameters fit well in the proportional odds ratio independence assumption, which means the relationship holds well across all the PWB categories within the model (as $p = 0.985$). The model showed a strong ability to predict the correlation between CPU_SMFeeling and PWB [Omnibus test chi-square (12) = 53.291, $p < 0.001$]. The ability of the model to predict the effect of CPU_SMFeeling on the PWB of undergraduate students was improved after controlling variables such as sex, ethnicity, college, age, years in college, CPU_Total, CPU_BeforeBed, CPU_Arousal, CPU_Switch, CPU_SRLBehavior, and CPU_SMResponse. As a result, the adjusted crude odds ratio of the model was increased and the CPU_SMFeeling was found to be a strong predictor of undergraduate students' PWB [Exp (B) = 1.913, $p < 0.001$]. It can be inferred from correlational and descriptive test-statistics that undergraduate students were occasionally able to relate to CPU_SMFeelings, which helped them to boost their PWB.

Table 4.7

Ordinal Logistic Regression Analyses Showing Relationship Between Cell Phone Use Variables (CPU_SMF and CPU_SMR) and Psychological Well Being (PWB) (N = 520)

Dependent Variable	Independent Variable	Odds Ratio	
		Crude OR (95% CI)	Adjusted OR (95% CI)[a]
PWB			
	CPU_SMF	1.798** (1.413 - 2.286)	1.913** (1.379 - 2.654)
	CPU_SMR	1.352* (1.115 - 1.641)	1.036 (0.799 - 1.343)

Note. CPU_SMF = Cell phone social media feeling, CPU_SMR = Cell phone social media response, CPU_Total = Total hours-per-day spent using cell phones, CPU_BeforeBed = The use of cell phone before sleep, CPU_Arousal = The use of cell phones for accessing sexually explicit, violently, or emotionally charged media content, CPU_Switch = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRL = The use of cell phones for self-regulated learning strategies, CPU_SMF = Cell phone social media feeling, CPU_SMR = Cell phone social media response.

[a] adjusted for sex, ethnicity, colleges, age, years in college, CPU_Total, CPU_BeforeBed, CPU_Arousal, CPU_Switch, CPU_SRL, CPU_SMF, and CPU_SMR.

*$p < 0.01$; **$p < 0.001$.

H3b: *We expect, according to Maslow's hierarchy of needs (psychological needs i. e. belonging and esteem needs), instant cell phone social media responses (likes, shares, and comments followed by emoji's, GIF's [Graphics Interchange Format images] or stickers) to relate positively to the PWB of undergraduate students.*

H3b was supported.

The cell phone social media response (CPU_SMResponse) was positively correlated with the PWB of undergraduate students (Spearman's coefficient = 0.126, $p < 0.001$) (Table 5). The crude odds ratio indicated that there are higher odds of PWB occurring with the CPU_SMResponse of undergraduate students [Exp (B) = 1.352, $p < 0.01$] (Table 7). However, the CPU_SMResponse parameters did not fit well in the proportional odds ratio independence assumption, which means that the relationships did not hold across all the PWB categories within the model (as $p = 0.000$). The ability of the model to predict the effect of CPU_SMResponse on the PWB of undergraduate students was reduced after controlling variables such as sex, ethnicity, college, age, years in college, CPU_Total, CPU_BeforeBed, CPU_Arousal, CPU_Switch, CPU_SRLBehavior, and CPU_SMResponse. The likelihood chi-square ratio [chi square (1) = 0.069, $p = 0.792$] and adjusted odds ratio were not statistically significant [Exp (B) = 1.036, $p = 0.792$] for the model. These results indicated that the CPU_SMResponse was not a significant predictor of the PWB of undergraduate students, however, it was noteworthy that CPU_SMResponse was correlated to the PWB, which supported the hypothesis, even though when factored in the controlling variables, the correlation was not as strong to predict the PWB. The correlational and descriptive statistics altogether revealed that undergraduate students were able to relate to CPU_SMResponses on a varied scale, which, therefore, increased their PWB.

4.2.4. The Estimates of Effect Size

The eta squared was used to determine effect size between the groups because this method takes all level categories into account (Lakens, 2013; Durlak, 2009). The effect size for correlations of all supported hypotheses is presented in Table 8. For a univariate ANOVA, the effect size for the outcome variable with an eta squared value of 0.01 is considered small, 0.06 is considered medium, and 0.14 is considered large (Lakens, 2013; "Rules of thumb on magnitudes of effect sizes," 2019).

The effect size estimates indicated that CPU_BeforeBed had a medium effect (eta squared = 0.09) on the sleep latency of undergraduate students. The effect size estimates also indicated that CPU_Arousal had a medium effect (eta squared = 0.13) on the sleep difficulty of undergraduate students. The eta squared value for the GPA of undergraduate students was not statistically significant ($p < 0.01$). Additionally, both CPU_SMFeeling and CPU_SMResponse had a medium (eta squared = 0.09) and a small (eta squared = 0.04) effect on the PWB of undergraduate students.

Table 4.8

Effect Size for Sleep Latency, Sleep Difficulty, Grade Point Average (GPA), and Psychological Well Being (PWB)

Tests of Between-Subjects Effects						
Outcome (Dependent Variable)	Experimenter Effect (Independent variable)	N	df	F	Eta Squared	Effect Size
Sleep Latency	CPU_BeforeBed	525	24	1.965	0.09*	Medium
Sleep Difficulty	CPU_Arousal	525	38	1.976	0.13*	Medium
GPA	CPU_Switch	524	110	1.189	0.24	N.S.[a]
PWB	CPU_SMF	520	24	2.054	0.09*	Medium
PWB	CPU_SMR	520	12	1.887	0.04*	Small

Note. CPU_Total = Total hours-per-day spent using cell phones, CPU_BeforeBed = The use of cell phone before sleep, CPU_Arousal = The use of cell phones for accessing sexually explicit, violently, or emotionally charged media content, CPU_Switch = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRL = The use of cell phones for self-regulated learning strategies, CPU_SMF = Cell phone social media feeling, CPU_SMR = Cell phone social media response.

[a]N.S. = Not statistically significant.

*$p < 0.01$.

5. DISCUSSION AND CONCLUSIONS

This study began with the following research questions: How does the CPU of undergraduate students correlate to their sleep latency and sleep difficulty? How does CPU for switching away from class/lecture, lab, and/or study sessions, and CPU for self-regulated learning behaviors correlate to undergraduate students' academic performance? How does the cell phone social media use of undergraduate students correlate to their psychological well-being? To answer these questions, six hypotheses were developed, two from each domain of outcome variables: sleep quality, academic performance, and psychological well-being. All six hypotheses were based on existing learning theories.

The following sections will present a rationale for supporting or refuting each hypothesis. These sections will also draw conclusions from the results pertaining to the domains as defined in the above paragraph.

5.1. CPU and Sleep Quality

There were two hypotheses in the domain of sleep quality. The first hypothesis, Sleep Latency, suggests that CPU for unstructured leisure activities before sleep (CPU_BeforeBed) relates positively to the sleep latency of undergraduate students. This hypothesis was supported because the odds ratio for sleep latency was statistically significant ($p < 0.001$) and positive. The increasing amount of CPU_BeforeBed caused an increase in the sleep latency of undergraduate students. However, female undergraduate students, as compared to male undergraduate students, stayed up late more often to use social media on their cell phones. Moreover, female undergraduate students, as compared to male undergraduate students, stayed up late more often to watch videos on their cell phones. These outcomes have great relevance to the population under examination due to the fact that 83% of college students use their cell phones within one hour of going to bed (Moulin and Chung, 2017).

The positive correlation between CPU_BeforeBed and sleep latency aligned with the sleep latency data of the present study. The sleep latency data showed that 73% of undergraduate students had some sort of sleep latency, with 36% on a higher-end who either could not sleep within one hour or more than one hour after going to bed (Table 3). An explanation of this sleep latency finding can be explained via the Sleep Displacement mechanism (Exelmans & Van den Bulk, 2016), i.e., displacement of sleep due to prior unstructured leisure activities. In these cases, the brain would believe it is still working, making an association between the location of CPU (i.e. the bed) and work (anything outside of sleep). Further, the sleep latency data from this study was congruent with the results of previous studies (Zarghami et al., 2015; Moulin & Chung, 2017), which revealed that CPU 'in bed' and CPU 'after lights were out' negatively influenced sleep patterns, provided that sleep latency was one of the key components of the overall sleep quality index. The CPU study provided the necessary support for the Sleep Displacement mechanism and inferred that the use of cell phones after a target bedtime resulted in higher risks of sleep latency in undergraduate students.

Data analysis showed that CPU_BeforeBed was the significant predictor of their sleep latency as a one-unit increase in CPU_BeforeBed predicted a 1.063 increase in sleep latency. The findings indicated that CPU_BeforeBed had a statistically significant effect ($p < 0.01$) with a medium effect size on the sleep latency of undergraduate students. Several other factors might have caused sleep latency as well, including awareness and compulsion to check cell phone notifications (Murdock et al., 2017; Li et al., 2015). Text messaging alone affected the sleep latency of undergraduate students and was found to be the mediator between CPU and sleep-related disorders, such as depression and anxiety (Adams and Kisler, 2013). With the established correlation between CPU_BeforeBed and sleep latency, our findings supported the Sleep Displacement Mechanism of sleep disruption proposed in previous studies (Exelmans & Van den Bulck, 2016; Clayton et al., 2015; Cain and Gardisar, 2010). It can be concluded that the use of cell phones for unstructured leisure activities before sleep is harmful to the undergraduate student demographic.

The second hypothesis postulates that the mental (cognitive), emotional or psychological arousal caused by CPU for accessing sexually explicit, violently, or emotionally charged media content before sleep (CPU_Arousal) relates positively to the sleep difficulty of undergraduate students. Referring to the literature review, no study was found that links the construct of CPU _Arousal with the sleep difficulty of undergraduate students. Previous studies focused on texting, calling, and social networking, (Mendoza, et al., 2018; Moulin & Chung, 2017; Murdock et al., 2017; Exelmans & Van den Bulk, 2016) but did not investigate violently or emotionally charged media content before sleep. Previous studies also investigated sexting (Fleschler Peskin et al., 2013), however, they did not cover sexually explicit media content.

The sleep difficulty hypothesis was supported and the odds ratio for sleep difficulty was statistically significant ($p < 0.001$) and positive. An increase in the use of cell phones for accessing explicit or emotionally charged media content before sleep increased the sleep difficulty of undergraduate students. Cain and Gardisar (2010) suggested that the use of electronic media, such as cell phones, just before sleep escalates mental (cognitive), emotional or psychological arousal. In other previous studies, violent and sexual media content in music, movies, television, magazines (Brown et al., 2006), and video games (Dill et al., 2005) were also identified as contributors to the arousal. In the presented study, however, male undergraduate students (3.71 ± 2.68), as compared to female undergraduate students (1.85 ± 1.72), were engaged more in explicit content pertaining to sexuality using their cell phones. Male undergraduate students (3.39 ± 2.65), as compared to female undergraduate students (1.94 ± 1.80) were also engaged more in explicit content pertaining to violence. In addition, male undergraduate students (2.50 ± 2.23), as compared to female undergraduate students (1.54 ± 1.32) stayed awake longer to engage in sexually-oriented cell phone apps. Male undergraduate students (2.28 ± 2.04), as compared to female undergraduate students (1.46 ± 1.29) also stayed awake longer to engage in violence-based cell phone apps. Concisely, the data from the CPU study provided the necessary support for the CPU Arousal mechanism, and it can be inferred that CPU_Arousal increased the sleep difficulty of undergraduate students.

In previous studies, constant connectivity was found as one of the key reasons that young adults were compelled to be available “around the clock,” even after going to bed (Thomee et al., 2010). Interacting with cell phones before sleep escalated emotional and/or mental (cognitive) arousal in undergraduate students and therefore increased their sleep difficulty (Thomee et al., 2010). The CPU study data showed that, of the undergraduate students who reported experiencing CPU_Arousal, 94.7% had some sort of sleep difficulty. CPU_Arousal was measured by their engagement with sexually explicit, violently, or emotionally charged media content and thinking about occurrences of these activities from earlier. Putting all this together concludes that the use of cell phones for accessing sexually explicit, violently, or emotionally charged media content before sleep increases sleep difficulty in young adults.

The ordinal logistic indicated that CPU_Arousal was a significant predictor of the sleep difficulty of undergraduate students; a one-unit increase in CPU_Arousal predicted a 1.064 increase in sleep difficulty. The CPU_Arousal had a statistically significant impact ($p < 0.01$) with a medium effect size on the sleep difficulty of undergraduate students. Taken together with previous studies focusing on electronic media in relation with mental (cognitive), emotional or psychological arousal (Cain and Gardisar, 2010), this study supports the notion that higher levels of CPU_Arousal are directly associated with the sleep difficulty of undergraduate students. With the established correlation between CPU_Arousal and sleep difficulty, the CPU study supported the media content mechanism of sleep disruption proposed in previous studies (Exelmans & Van den Bulck, 2016; Clayton et al., 2015; Cain and Gardisar, 2010).

5.2. CPU and Academic Performance

There were two hypotheses in the domain of academic performance. The first hypothesis, CPU Switch, proposes that the frequency of cell phone checking during a class/lecture, lab and/or study session (CPU_Switch) relates negatively to the academic performance (GPA) of undergraduate students. This hypothesis was supported because CPU_Switch was found to be negatively correlated with the GPA of undergraduate students. These results were consistent with the previous studies demonstrating the associations between CPU_Switch and GPA (Rosen et al., 2013; Jacobsen & Forste, 2011) of college students.

The descriptive analysis of GPA (Table 2) showed that during a 60-minute class/lecture, lab, and/or study session, undergraduate students switched tasks from studying to checking their cell phones around four times. Switching between two relatively unfamiliar tasks, such as class/lecture and CPU, costs them efficiency, known as switch cost (Rubinstein et al., 2001). Further, the switch cost adds up to a large amount when switched between tasks multiple times, therefore, it may result in difficulty focusing on complex tasks such as class/lecture and/or study. With the available data and the established correlation between CPU switch and GPA, the presented study endorses previous research that examined the impact of CPU switch on GPA and affirms the fact that switching between CPU and class/lecture/study impacts GPA negatively.

Unlike previous studies (Li et al., 2015; Bjornsen & Archer, 2015), the CPU study did not find switching between CPU and class/lecture and/or study session a significant predictor of academic performance. Moreover, the findings indicated that

CPU_Switch had no statistically significant effect ($p = 0.117$) on the GPA of undergraduate students. Like Li et al. (2015), who have found in-class CPU a negative predictor of GPA, the presented study uses the overall current collegiate GPA of undergraduate students as a measure of academic performance. The other studies (Bjornsen & Archer, 2015) have used the test grades from one course and have found the factors such as understanding of class content and being interested in class/lecture predicted the test grades positively while using social media and playing games did so negatively. However, Bjornsen and Archer have found that using the internet and organizing tools (e. g., updating one's calendar) did not predict the test grades. Taking together previous studies (Mendoza et al., 2018; Felisoni & Godoi, 2018) and the CPU study, it can be concluded that the use of cell phones during class/lecture and/or study session causes a distraction (Blasiman, et al., 2018; Fernandez, 2018) and affects academic performance negatively (Han & Yi, 2018; Pettijohn et al., 2015; Li et al., 2015), but is not a significant predictor of the academic performance of undergraduate students.

The second hypothesis asserts that the use of cell phones for self-regulated learning strategies (metacognitive, motivational, and behavioral) (CPU_SRLBehavior) relates positively to the academic performance (i.e., college GPA) of undergraduate students. This hypothesis was not supported as the CPU_SRLBehavior was unrelated to the GPA of undergraduate students. These results aligned with the finding from a previous study on the self-regulated learning behaviors of university students, in which authors Yot-Domínguez and Marcelo (2017) stated that "even when they [university students] are frequent users of digital technology, they tend not to use these technologies to regulate their own learning process.” Concluding the results of the CPU study, the CPU for self-regulated learning strategies, such as using an alarm, calendar, calculator, notes, Google Docs, timer, emails, and texts did not affect undergraduate students’ academic performance.

College students believe that the use of cell phones enhances their learning processes and makes them more productive (Fernandez, 2018), provided the fact that CPU perceptions for learning were different than the actual CPU. Previous studies have assessed actual classroom CPU of college students and revealed that college students were hugely distracted by CPU, particularly texting (Mendoza et al., 2018), Facebook’ing, and Twitter’ing (Wood, 2018). Smartphone self-efficacy and behavioral intentions ("a person's perceived likelihood that he or she will be engaged in a particular behavior") to use smartphones were positively related to cell phone mediated communication (Han & Yi, 2018). However, the impacts of these variables on the academic performance of college students were unknown. The CPU study revealed that female undergraduate students, as compared to male undergraduate students, had higher mean scores for CPU_SRL strategies, such as alarm, timer/stopwatch/clock, and email and social media. The CPU study also revealed that Asian undergraduate students, as compared to Latinx and Caucasian undergraduate students, had higher mean scores for CPU_SRL strategies: calendar, notes, Google docs, email and social media, and texts. The CPU_SRL strategies, however, did not affect the academic performance of undergraduate students.

The social cognitive views of self-regulated academic learning, based on the model of triadic reciprocal determinism, emphasized that personal, behavioral, and environmental factors influence human behavior (Zimmerman, 1989). Further, "the major self-regulative mechanism operates through three principal subfunctions. These include self-monitoring of one's behavior, its determinants, and its effects; judgment of one's behavior concerning personal standards and environmental circumstances; and affective self-reaction" (Bandura, 1991, p. 248). The cell phone activities, such as using an alarm, calendar, calculator, notes, Google Docs, timer, emails, and texts may be helpful to regulate habits, however, they do not help regulate the learning process driven by the self-regulative mechanism proposed by Bandura and Zimmermann. CPU self-regulated activities might have helped monitor one's self (personal) but did not seem to influence determinants such as "judgment of one's behavior" and "environmental circumstances." More research is needed to explore the ways digital technology like cell phones can help regulate learning processes, especially during unprecedented times like the COVID-19 pandemic ("Coronavirus disease 2019 (COVID-19)," 2020), when virtual education platforms (Zoom, Cisco Webex, Hangout, etc.) are used to lead instruction in higher education classrooms.

5.3. CPU and Psychological Well-Being

There were two hypotheses in the domain of PWB. The first hypothesis, CPU Social Media Feeling (CPU_SMFeeling), holds that the CPU_SMFeeling relates positively (due to constant accessibility of cell phones) to the PWB of undergraduate students. This hypothesis was supported because the Spearman coefficient for

CPU_SMFeeling was positive, which indicates that CPU_SMFeeling was positively correlated with the PWB of undergraduate students. An increase in CPU_SMFeeling (such as engagement and connectedness, competency and accomplishment, pleasure and sense of enjoyment, sense of purpose and fulfillment, sense of belonging and acceptance, and optimism about the future) increased the PWB of undergraduate students. This hypothesis was also supported because the odds ratio for CPU_SMFeeling was statistically significant ($p < 0.001$) and positive, which means the increasing amount of CPU_SMFeeling caused an increase in the PWB of undergraduate students.

The outcomes of this hypothesis were crucial being that it was the first time the use of cell phones for social media was assessed using measures aligned to the states of effective human functioning, i.e., PWB. The descriptive analyses of CPU_SMFeeling (Table 2) indicated that the occasional use of cell phones for social media (Instagram, Twitter, Facebook, Snapchat, LinkedIn, etc.) helped undergraduate students feel connected, competent, and optimistic. Undergraduate students found social media apps interesting and meaningful, and the use of social media on cell phones often helped them feel pleasure and a sense of enjoyment, a sense of purpose and fulfillment, as well as a sense of belonging and acceptance, with Asian undergraduate students, as compared to Caucasian undergraduate students, having higher CPU_SMF scores. These results align with the previous research (Park & Lee, 2012), which found ‘connecting with others’ as one of the motives for CPU. Moreover, this study supported the notion that CPU helps reduce loneliness (Park & Lee, 2012), as the use of cell phones for social media helped undergraduate students feel engaged and connected.

Ordinal logistic of the CPU study indicated that CPU_SMFeeling was a strong predictor of the PWB in undergraduate students; a one-unit increase in CPU_SMFeeling predicted a 1.913 increase in PWB. In alignment with these results, the CPU_SMFeeling had a statistically significant impact ($p < 0.01$) with a medium effect size on the PWB of undergraduate students. This means that increased levels of CPU_SMFeeling helped undergraduate students rank themselves as having more psychological resources and strengths. These outcomes endorsed previous research (Chen and Li, 2017) that found communicative CPU, including social media, beneficial for PWB. Further, considering the fact that the use of cell phones for emotion regulation affect well-being positively (Hoffner & Lee, 2015), and the locus of control impacts satisfaction with life positively (Li et al., 2015), it can be concluded that the use of cell phones helps undergraduate students improve their socio-psychological prosperity. Referring to the descriptive analyses of this study (Table 2), CPU_SMFeeling helped undergraduate students feel competent and accomplished, and moreover, had a sense of purpose and fulfillment. Altogether these results show that the CPU_SMFeeling hypothesis supported the Six-factor Model of Psychological Well-Being (Ryff, 1989), and it can be established that the use of cell phones for social media helps undergraduate students improve their PWB.

The second hypothesis states that instant cell phone social media responses (likes, shares, and comments followed by emoji's, GIF's [Graphics Interchange Format images] or stickers) relates positively to the PWB of undergraduate students. This hypothesis was supported because the positive Spearman coefficient for

CPU_SMResponse indicates a positive correlation with the PWB of undergraduate students. An increase in CPU_SMResponse, such as connecting with others, contributing to the well-being of others (by liking, sharing, loving, using emojis, posting GIF's, attaching stickers, etc.,), feeling liked, and feeling rewarded, increased the PWB of undergraduate students. This hypothesis was also supported because the odds ratio for CPU_SMResponse was statistically significant ($p < 0.01$) and positive, which means, the increasing amount of CPU_SMResponse caused an increase in the PWB of undergraduate students.

The CPU_SMResponse had a statistically significant impact ($p < 0.01$) with a small effect size on the PWB of undergraduate students. The descriptive analyses of CPU_SMResponse (Table 2), which indicated that undergraduate students feel liked when others respond to their posts on social media more frequently, supported the effect size analysis. The descriptive analyses also suggested that cell phone social media engagements helped undergraduate students feel connected, rewarded, and contributive to the well-being of others when they actively respond to others' posts on social media more than occasionally. It may be due to these reasons that the socio-psychological prosperity of more extroverted users was higher than that of less extroverted users (Park & Lee, 2012). For these reasons, it can be concluded that the correlation between CPU_SMResponse and PWB supports the Maslow Hierarchy of Psychological Needs (Maslow, 1987), which includes the feeling of belongingness including affiliation, social interaction, friendship, giving and receiving, and contributions to the well-being of others.

Ordinal logistic regression indicated that CPU_SMResponse did not predict the PWB of undergraduate students as the adjusted odds ratio for CPU_SMResponse was not statistically significant ($p = 0.792$). An increased level of CPU_SMResponse did not predict whether or not undergraduate students ranked themselves as having more psychological resources and strengths. These outcomes resonate with the outcomes of the previous research (Kumcagiz & Gunduz, 2016) on cell phone addiction (smartphone addiction in the case of smartphone users) and PWB. Kumcagiz and Gunduz (2016) have reported that high smartphone users had lower levels of PWB than that of low smartphone users. It might have been the case that overwhelming CPU_SMResponses jeopardized their social relationships, as excessive online communication inversely affected well-being (Chan, 2013). Limited research in this area restricts justification and caution while interpreting results. Future research with more quantifiable measures of CPU_SMResponse would help us understand whether or not CPU_SMResponse predicts the PWB of undergraduate students.

5.4. Limitations

While this study has produced several novel and practical findings, there are limitations to be considered when interpreting the results. The sample, comprised of undergraduate students from a single public university in the Southwestern United States, may reflect some demographic, socio-economic, and cultural specificities. For example, women comprised 75.4% of participants in the CPU study sample whereas the population of women undergraduate students attending TAMU and larger US population consist of 46.6% and 50.8%, respectively ("Student data and reports," n.d.; "U.S. Census

Bureau QuickFacts: United States," n.d.). The CPU study may have suffered from the overrepresentation of female participants, which might have influenced the outcomes. The percentage of Caucasian undergraduate students was highest (45.9%) in the CPU study. This data somehow goes in parallel proportion to the TAMU population (58.6% Caucasian) and the US population (60.4% Caucasian). However, the study may reflect the cultural specificities of the Caucasian population more than any other ethnic group in the sample.

The CPU study sample comprised 20.4% Asian undergraduate student participation compared to the 8.6% Asian undergraduate student population at TAMU and 5.9% Asian population in the US. This overrepresentation may reflect the socio-economic and cultural specificities of the Asian population pertaining to the use of cell phones. Lastly, the percentage of African American undergraduate students was 3.2%, which is in a similar proportion of the TAMU population of African American students (3.2%), but different in the percentage of African Americans (13.4%) in the United States ("U.S. Census Bureau QuickFacts: United States," n.d.). This underrepresentation may have restricted the outcomes from reflecting the socio-economic and cultural specificities of African American participants and limited practical implications for the stated ethnic demographic.

The self-reported measures lead to another limitation of this study. Recall bias (Hassan, 2006) is the key concern about self-reported questionnaires; however, other factors occurring while participants took the survey including daily routine, non-academic workload, studies, leisure activities, family and social commitments cannot be ruled out. In addition, self-reported measures may have limitations due to a number of reasons, such as honesty/image management, introspective ability, understanding, rating scales, response bias, and sampling bias (Hoskin, 2012). Limitations concerning honesty/image management appear when participants try to report more socially acceptable responses or want to manage their responses [in a way that appears favorable]. Biases due to the introspective ability appear when, despite being honest, a participant provides an incorrect response due to the lack of introspective ability, i.e., the ability to assess "self" completely accurately.

Another limitation of self-reporting is that different participants may interpret questions differently, which may lead to unintended bias. The rating scale could also lead some participants to respond with extremes on the scale (Austin et al., 1998) or "hug around the midpoints" (Hoskin, 2012). The study measures are subjected to the response bias irrespective of participants' experiences about actual situations. The study measures may also pose limitations if the items are based on the ordinal scale of measurement as the ordinal data tells the order but not the distance between the responses. Lastly, online self-reported data may have sampling bias because the researcher loses control over the makeup of their sample.

Despite several merits, the CPU study instrument might have lacked quantifiable measures, especially for CPU variables of unsupported hypotheses. The measures of CPU_SRLBehavior assessed the use of cell phones for self-regulated learning strategies, such as using an alarm, calendar, calculator, notes, Google Docs, timer, emails, and texts. It could be the self-regulated learning processes (i.e., goal-setting, self-monitoring, and self-reflection (Zimmerman, 2000)) that are more quantifiable measures of CPU variables concerning self-regulation, and correlate to the academic performance of undergraduate students. Additionally, due to the nature of the study, causality cannot be confirmed from the results. Finally, as the CPU research is in its infancy, it is likely that future research will identify additional CPU factors concerning sleep quality, academic performance and PWB of young adults, and the instrument used in the present study will be modified to account for the unsupported hypotheses in this study or for new hypotheses in future studies.

5.5. Recommendations

Both subjective (quantitative surveys, reflections, sleep diaries, etc.) and objective (clinical assessments, embedded sensors, and built-in cell phone sensing apps) assessment methods should be used to gain a detailed, comprehensive and in-depth understanding of CPU. The cell phone operating system records (i.e., physical activity, social interaction, mobility, sleep, and CPU) should also be used to better understand CPU behaviors. Varied samples from both college and non-college settings and across majors should help see the difference in CPU patterns across young adult demographics. More quantifiable measures using the latest cell phone activities/operations will help assess changing trends in CPU over time. Linking CPU measures/variables to existing theories will help provide a theoretical basis to CPU research. Finally, and importantly, future researchers should rely more on longitudinal data as it will have more clinical and practical relevance.

Young adults might be the most vulnerable population to the harmful effects of CPU as the largest demographic (PEW Research Center, 2018). CPU was found to have established associations with the cognitive, emotional, and PWB of young adults. Future research into how CPU and cell-phone-mediated-communication (CPMC) affects the social-emotional learning of young adults should be the next step. Examining the role of CPMC as an emotional stimulus could be another area for future research. A better understanding of CPMC will help in developing responsible decision-making skills necessary for social awareness in the digital age. The broader goal should be to ensure that all students – particularly those from historically marginalized backgrounds - have a better understanding of the use of cell phones and CPMC for enhanced social-emotional learning.

The CPU study data was collected in the fall of 2019, and the analysis was conducted in the spring of 2020 in the midst of the COVID-19 global pandemic. Some study measures, especially from the domains of academic performance and PWB, may lead to interesting and better-informed outcomes post COVID-19. As "we will come back from COVID-19 with a much more widely shared understanding that digital tools are complements, not substitutes, for the intimacy and immediacy of face-to-face learning," says Joshua Kim, Director of Online Programs and Strategy at the Dartmouth Center for the Advancement of Learning ("Teaching and learning after COVID-19," 2020). It would be interesting to see if the data is comparable after three semesters (Spring, Summer I & II) of virtual education. Another investigation of the CPU study is warranted considering the global conversion to virtual education through remote learning due to the COVID-19 pandemic. Additionally, the face of classroom CPU (CPU_Switch, etc.), CPU self-regulated behavior, and cell phone social media could portray a different picture altogether post COVID-19; therefore, they need to be examined once we are back into the mainstream after this pandemic.

REFERENCES

Adams, S. K., & Kisler, T. S. (2013). Sleep quality as a mediator between technology-related sleep quality, depression, and anxiety. *Cyberpsychology, Behavior, and Social Networking*, *16*(1), 25-30. doi:10.1089/cyber.2012.0157

Al–Ali, B. M., Patzak, J., Fischereder, K., Pummer, K., & Shamloul, R. (2013). Cell phone usage and men's erectile dysfunction: A short communication. *Central European Journal of Urology, 66*(1), 75-77. doi:10.5173/ceju.2013.01.art23

Al-Khamees, N. (2007). A study in Kuwait of health risks associated with using cell phones. *College Student Journal*, *41*(1), 187-203.

Anderson, C. A., Shibuya, A., Ihori, N., Swing, E. L., Bushman, B. J., Sakamoto, A., … Saleem, M. (2010). Violent video game effects on aggression, empathy, and prosocial behavior in Eastern and Western countries: A meta-analytic review. *Psychological Bulletin*, *136*(2), 151-173. doi:10.1037/a0018251

Andrews, F. M., & Withey, S. B. (1976). Americans' well-being: Life-as-a-whole. *Social Indicators of Well-Being*, 309-335. doi:10.1007/978-1-4684-2253-5_10

Americans' views on mobile etiquette. (2015). Retrieved from http://www.pewinternet.org/2015/08/26/americans-views-on-mobile-etiquette/

Austin, E. J., Deary, I. J., Gibson, G. J., McGregor, M. J., & Dent, J. (1998). Individual response spread in self-report scales: personality correlations and consequences. *Personality and Individual Differences*, *24*(3), 421-438. doi:10.1016/s0191-8869(97)00175-x

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice Hall.

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational Behavior and Human Decision Processes*, *50*(2), 248-287. doi:10.1016/0749-5978(91)90022-l

Beal, V. (2008). The difference between a cellular phone, smartphone, and PDA. Retrieved from https://www.webopedia.com/DidYouKnow/Hardware_Software/smartphone_cellphone_pda.asp

Berry, M. J., & Westfall, A. (2015). Dial D for distraction: The making and breaking of cell phone policies in the college classroom. *College Teaching*, *63*(2), 62–71. doi:10.1080/87567555.2015.1005040

Billieux, J. (2012). Problematic use of the mobile phone: A literature review and a pathways model. *Current Psychiatry Reviews*, *8*(4), 299–307.

Bjornsen, C. A., & Archer, K. J. (2015). Relations between college students' cell phone use during class and grades. *Scholarship of Teaching and Learning in Psychology*, *1*(4), 326–336. doi:10.1037/stl0000045

Blask, D. E., Sauer, L. A., Dauchy, R. T., Holowachuk, E. W., & Ruhoff, M. S. (1999). New insights into melatonin regulation of cancer growth. *Advances in Experimental Medicine and Biology*, 337-343. doi:10.1007/0-306-46814-x_38

Bollen, K. A. (2014). *Structural Equations with Latent Variables*. Hoboken, NJ: John Wiley & Sons.

Braguglia, K. H. (2011). Cellular telephone use: A survey of college business students. *Journal of College Teaching & Learning (TLC)*, *5*(4). doi:10.19030/tlc.v5i4.1279

Brainard, G. C., Hanifin, J. P., Rollag, M. D., Greeson, J., Byrne, B., Glickman, G., … Sanford, B. (2001). Human melatonin regulation is not mediated by the three cone photopic visual system. *The Journal of Clinical Endocrinology & Metabolism*, *86*(1), 433-436. doi:10.1210/jcem.86.1.7277

Brown, J. D., L'Engle, K. L., Pardun, C. J., Guo, G., Kenneavy, K., & Jackson, C. (2006). Sexy media matter: Exposure to sexual content in music, movies, television, and magazines predicts black and white adolescents' sexual behavior. *Pediatrics*, *117*(4), 1018-1027. doi:10.1542/peds.2005-1406

Brown, S. L., Nesse, R. M., Vinokur, A. D., & Smith, D. M. (2003). Providing support may be more beneficial than receiving it: Results from a prospective study of mortality. *Psychological Science*, *14*, 320–327. doi:10.1111/1467-9280.14461.

Buysse, D. J., Reynolds, C. F., Monk, T. H., Berman, S. R., & Kupfer, D. J. (1989). The Pittsburgh sleep quality index: A new instrument for psychiatric practice and research. *Psychiatry Research*, *28*(2), 193-213. doi:10.1016/0165-1781(89)90047-4

Cain, N., & Gradisar, M. (2010). Electronic media use and sleep in school-aged children and adolescents: A review. *Sleep Medicine*, *11*(8), 735-742. doi:10.1016/j.sleep.2010.02.006

Cajochen, C., Münch, M., Kobialka, S., Kräuchi, K., Steiner, R., Oelhafen, P., … Wirz-Justice, A. (2005). High sensitivity of human melatonin, alertness, thermoregulation and heart rate to short wavelength light. *The Journal of Clinical Endocrinology & Metabolism*, *90*(3), 1311-1316. doi:10.1210/jc.2004-0957

Cajochen, C., Jud, C., Münch, M., Kobialka, S., Wirz-Justice, A., & Albrecht, U. (2006). Evening exposure to blue light stimulates the expression of the clock gene PER2 in humans. *European Journal of Neuroscience*, *23*(4), 1082-1086. doi:10.1111/j.1460-9568.2006.04613.x

Campbell, A, (1976). Subjective measures of well-being. *American Psychologist, 31,* 117-124.

Chan, M. (2013). Mobile phones and the good life: Examining the relationships among mobile use, social capital and subjective well-being. *New Media & Society*, *17*(1), 96-113. doi:10.1177/1461444813516836

Chellappa, S. L., Steiner, R., Oelhafen, P., Lang, D., Götz, T., Krebs, J., & Cajochen, C. (2013). Acute exposure to evening blue-enriched light impacts on human sleep. *Journal of Sleep Research*, *22*(5), 573-580. doi:10.1111/jsr.12050

Chen, H., & Li, X. (2017). The contribution of mobile social media to social capital and psychological well-being: Examining the role of communicative use, friending and self-disclosure. *Computers in Human Behavior*, *75*, 958-965. doi:10.1016/j.chb.2017.06.011

Chen, H. T., & Chen, W. (2015). Couldn't or wouldn't? The influence of privacy concerns and self-efficacy in privacy management on privacy protection. *Cyberpsychology, Behavior, and Social Networking, 18*(1), 13e19.

Chow, H. P. (2010). Predicting academic success and psychological wellness in a sample of Canadian undergraduate students. *Electronic Journal of Research in Education Psychology*, *8*(2), 473-496.

Clayton, R. B., Leshner, G., & Almond, A. (2015). The extended iSelf: The impact of iPhone separation on cognition, emotion, and physiology. *Journal of Computer-Mediated Communication*, *20*(2), 119-135. doi:10.1111/jcc4.12109

College enrollment statistics and student demographic statistics. (2019, June 7). Retrieved from https://educationdata.org/college-enrollment-statistics/

Common Data Set 2019-2020. (2019). Retrieved from https://dars.tamu.edu/Student/files/2019-2020-Common-Dataset.aspx

Coronavirus disease 2019 (COVID-19). (2020, April 3). Retrieved April 7, 2020, from https://www.cdc.gov/coronavirus/2019-ncov/index.html

Csikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience*. New York: Harper & Row.

Demirci, K., Akgönül, M., & Akpinar, A. (2015). Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. *Journal of Behavioral Addictions, 4*(2), 85-92. doi:10.1556/2006.4.2015.010

Demographics of internet and home broadband usage in the United States. (2018, February 5). Retrieved from https://www.pewinternet.org/fact-sheet/internet-broadband/

De-Sola Gutiérrez, J., Rodríguez de Fonseca, F., & Rubio, G. (2016). Cell-phone addiction: A review. *Frontiers in Psychiatry*, *7*. doi:10.3389/fpsyt.2016.00175

Detecting Multicollinearity using variance inflation factors. (n.d.). Retrieved from https://online.stat.psu.edu/stat462/node/180/

Diener, E. (1984). Subjective well-being. *Psychological Bulletin*, *95*, 542-575.

Diener, E. D., Emmons, R. A., Larsen, R. J, & Griffin, S. (1985). The satisfaction of life scale. *Journal of Personality Assessment*, *49*(1), 71-75.

Diener, E., Wirtz, D., Tov, W., Kim-Prieto, C., Choi, D., Oishi, S., & Biswas-Diener, R. (2009). New well-being measures: Short scales to assess flourishing and positive and negative feelings. *Social Indicators Research*, *97*(2), 143-156. doi:10.1007/s11205-009-9493-y

Diener E, Wirtz D, Biswas-Diener R, Tov, W., Kim-Prieto, C., Choi, D., & Oishi, S. (2009). New measures of well-being. In: Diener E (ed.) *Assessing Well-Being: The Collected Works of Ed Diener*. Champaign, IL: Springer, pp. 247–266.

Dill, K. E., Gentile, D. A., Richter, W. A., & Dill, J. C. (2005). Violence, sex, race, and age in popular video games: A content analysis. In: Cole, E., Henderson, D.J. (Eds.). American Psychological Association, Washington, DC. *Featuring females: Feminist analyses of media*, 115-130. doi:10.1037/11213-008

Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, phone, mail, and mixed-mode surveys: The tailored design method* (4th ed.). John Wiley & Sons.

Dowdell, E. B., & Clayton, B. Q. (2018). Interrupted sleep: College students sleeping with technology. *Journal of American College Health*, 1-7. doi:10.1080/07448481.2018.1499655

Drost, E. (2011). Validity and Reliability in Social Science Research. *Education Research and Perspectives*, *38*(1), 105-123.

Dunn, E., Aknin, L. B., & Norton, M. I. (2008). Spending money on others promotes happiness. *Science*, 319, 1687–1688. doi:10.1126/science.1150952.

Durlak, J. A. (2009). How to Select, Calculate, and Interpret Effect Sizes. *Journal of Pediatric Psychology*, *34*(9), 917-928. doi:10.1093/jpepsy/jsp004

Dworak, M., Schierl, T., Bruns, T., & Struder, H. K. (2007). Impact of singular excessive computer game and television exposure on sleep patterns and memory performance of school-aged children. *Pediatrics*, *120*(5), 978-985. doi:10.1542/peds.2007-0476

Elder, A. D. (2013). College students' cell phone use, beliefs, and effects on their learning. *College Student Journal*, *47*(4), 585–592.

Exelmans, L., & Van den Bulck, J. (2016). Bedtime mobile phone use and sleep in adults. *Social Science & Medicine*, *148*, 93-101. doi:10.1016/j.socscimed.2015.11.037

Eyvazlou, M., Zarei, E., Rahimi, A., & Abazari, M. (2016). Association between overuse of mobile phones on quality of sleep and general health among occupational health and safety students. *Chronobiology International*, *33*(3), 293-300. doi:10.3109/07420528.2015.1135933

Felisoni, D. D., & Godoi, A. S. (2018). Cell phone usage and academic performance: An experiment. *Computers & Education*, *117*, 175-187. doi:10.1016/j.compedu.2017.10.006

Fernandez, S. (2018). University student's perspectives on using cell phones in classrooms - Are they dialing up disaster? *The Turkish Online Journal of Educational Technology, 17*(1), 246-258.

Fleschler Peskin, M., Markham, C. M., Addy, R. C., Shegog, R., Thiel, M., & Tortolero, S. R. (2013). Prevalence and Patterns of Sexting Among Ethnic Minority Urban High School Students. *Cyberpsychology, Behavior, and Social Networking*, *16*(6), 454-459. doi:10.1089/cyber.2012.0452

For most smartphone users, it's a 'round-the-clock' connection. (2017). Retrieved from https://www.reportlinker.com/insight/smartphone-connection.html

Froese, A. D., Carpenter, C. N., Inman, D. A., Schooley, J. R., Barnes, R. B., Brecht P. W., & Chacon, J. D. (2012). Effects of classroom cell phone use on expected and actual learning. *College Student Journal, 46*(2), 323–332.

Gamio, A. (2016, September). Latinx: A Brief Guidebook. Retrieved from https://www.academia.edu/29657615/Latinx_A_Brief_Guidebook

Gaultney, J. F. (2010). The prevalence of sleep disorders in college students: Impact on academic performance. *Journal of American College Health*, *59*(2), 91-97. doi:10.1080/07448481.2010.483708

Gingerich, A. C., & Lineweaver, T. T. (2014). OMG! Texting in class = U Fail :(empirical evidence that text messaging during class disrupts comprehension. *Teaching of Psychology*, *41*(1), 44–51. doi:10.1177/0098628313514177

Gomes, A. A., Tavares, J., & De Azevedo, M. H. (2011). Sleep and academic performance in undergraduates: A multi-measure, multi-predictor approach. *Chronobiology International*, *28*(9), 786-801. doi:10.3109/07420528.2011.606518

Han, S., & Yi, Y. J. (2018). How does the smartphone usage of college students affect academic performance? *Journal of Computer Assisted Learning*, *35*(1), 13-22. doi:10.1111/jcal.12306

Harada, T., Morikuni, M., Yoshi, S., Yamashita, Y., and Takeuchi H. (2002). Usage of mobile phone in the evening or at night makes Japanese students evening-typed and night sleep uncomfortable. *Sleep and Hypnosis*, *4*(4), 149-153.

Harada, T., Tanoue, A., & Takeuchi, H. (2006). Epidemiological studies on dreams, sleep habits and mental symptoms in students aged 18-25 years and the 24 hour a day commercialization of Japanese society (1). *Sleep and Biological Rhythms*, *4*(3), 274-281. doi:10.1111/j.1479-8425.2006.00232.x

Harman, B. A., & Sato, T. (2011). Cell phone use and grade point average among undergraduate university students. *College Student Journal*, *45*(3), 544–549.

Hassan, E. (2006). Recall Bias can be a Threat to Retrospective and Prospective Research Designs. *The Internet Journal of Epidemiology*, *3*(2), 1-7. doi:10.5580/2732

Hayley, A. C., Sivertsen, B., Hysing, M., Vedaa, O., & Overland, S. (2017). Sleep difficulties and academic performance in Norwegian higher education students. *British Journal of Educational Psychology*, *87*(4), 722-737. doi:10.1111/bjep.12180

Hoffner, C. A., & Lee, S. (2015). Mobile phone use, emotion regulation, and well-being. *Cyberpsychology, Behavior, and Social Networking*, *18*(7), 411-416. doi:10.1089/cyber.2014.0487

Hong, F., Chiu, S., & Huang, D. (2012). A model of the relationship between psychological characteristics, mobile phone addiction and use of mobile phones by Taiwanese university female students. *Computers in Human Behavior*, *28*(6), 2152-2159. doi:10.1016/j.chb.2012.06.020

Hoskin, R. (2012, March 3). The dangers of self-report. Retrieved from https://www.sciencebrainwaves.com/the-dangers-of-self-report/

Howell, A. J., Digdon, N. L., Buro, K., & Sheptycki, A. R. (2008). Relations among mindfulness, well-being, and sleep. *Personality and Individual Differences*, *45*(8), 773-777. doi:10.1016/j.paid.2008.08.005

Hysing, M., Pallesen, S., Stormark, K. M., Jakobsen, R., Lundervold, A. J., & Sivertsen, B. (2015). Sleep and use of electronic devices in adolescence: results from a large population-based study. *BMJ Open*, *5*(1), e006748-e006748. doi:10.1136/bmjopen-2014-006748

ITU World telecommunication/ICT indicators database. (2018). Global ICT developments, 2001–2018. Retrieved from http://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx

Jacobsen, W. C., & Forste, R. (2011). The wired generation: Academic and social outcomes of electronic media use among university students. *Cyberpsychology, Behavior, and Social Networking*, *14*(5), 275–280.

Jia, Y., Chen, S., Deutz, N. E., Bukkapatnam, S. T., & Woltering, S. (2018). Examining the structure validity of the Pittsburgh Sleep Quality Index. *Sleep and Biological Rhythms*, 1-13. doi:10.1007/s41105-018-00201-0

Jenkins-Guarnieri, M. A., Wright, S. L., & Johnson, B. D. (2013). Development and validation of the Social Media Use Integration Scale. *Psychology of Popular Media Culture*, *2*(1), 38-50. doi:10.1037/e638312012-001

Junco, R., & Cotten, S. R. (2012). No A 4 U: The relationship between multitasking and academic performance. *Computers & Education*, *59*(2), 505-514. doi:10.1016/j.compedu.2011.12.023

Katz, L., & Lambert, W. (2016). A happy and engaged class without cell phones? It’s easier than you think. *Teaching of Psychology*, *43*(4), 340–345. doi:10.1177/0098628316662767

Kim, J. H. (2006). Currents in internet addiction. *Journal of Korean Medical Association*, *49*(3), 202–208.

King, D. L., Gradisar, M., Drummond, A., Lovato, N., Wessel, J., Micic, G., … Delfabbro, P. (2013). The impact of prolonged violent videogaming on adolescent sleep: An experimental study. *Journal of Sleep Research*, 22, 137–143.

King, A. L. S., Valença, A. M., Silva, A. C., Sancassiani, F., Machado, S., & Nardi, A. E. (2014). “Nomophobia”: Impact of cell phone use interfering with symptoms and emotions of individuals with panic disorder compared with a control group. *Clinical Practice and Epidemiology in Mental Health, 10*(1), 28–35. doi:10.2174/1745017901410010028

Kotzé, M., & Kleynhans, R. (2013). Psychological well-being and resilience as predictors of first-year students' academic performance. *Journal of Psychology in Africa*, *23*(1), 51-59. doi:10.1080/14330237.2013.10820593

Kubey, R. W. (1986). Television use in everyday life: Coping with unstructured time. *Journal of Communication, 36*(3), 108-123. doi:10.1111/j.1460-2466.1986.tb01441.x

Kumcagiz, H., & Gunduz, Y. (2016). Relationship between psychological well-being and smartphone addiction of university students. *International Journal of Higher Education, 5*(4). doi:10.5430/ijhe.v5n4p144

Kuncel, N. R., Credé, M., & Thomas, L. 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.

Kwon, M., Lee, J., Won, W., Park, J., Min, J., Hahn, C., … Kim, D. (2013). Development and validation of a smartphone addiction scale (SAS). *PLoS ONE, 8*(2), e56936. doi:10.1371/journal.pone.0056936

Kwon, M., Kim, D., Cho, H., & Yang, S. (2013). The smartphone addiction scale: Development and validation of a short version for adolescents. *PLoS ONE, 8*(12), e83558. doi:10.1371/journal.pone.0083558

Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science: a practical primer for t-tests and ANOVAs. *Frontiers in Psychology*, *4*, 1-12. doi:10.3389/fpsyg.2013.00863

Lawson, D., & Henderson, B. B. (2015). The costs of texting in the classroom. *College Teaching*, *63*(3), 119–124. doi:10.1080/87567555.2015.1019826

Lepp, A., Barkley, J. E., Sanders, G. J., Rebold, M., & Gates, P. (2013). The relationship between cell phone use, physical and sedentary activity, and cardiorespiratory fitness in a sample of U.S. college students. *International Journal of Behavioral Nutrition and Physical Activity*, *10*, Article 79. Retrieved from http://www.ijbnpa.org/content/10/1/79

Lepp, A., Barkley, J., & Karpinski, A. (2014). The relationship between cell phone use, academic performance, anxiety, and satisfaction with life in college students. *Computers in Human Behavior, 31*, 343–350.

Lepp, A., Barkley, J. E., & Karpinski, A. C. (2015). The relationship between cell phone use and academic performance in a sample of U.S. college students. *SAGE Open*, *5*(1), 215824401557316. doi:10.1177/2158244015573169

Li, J., Lepp, A., & Barkley, J. E. (2015). Locus of control and cell phone use: Implications for sleep quality, academic performance, and subjective well-being. *Computers in Human Behavior*, *52*, 450-457. doi:10.1016/j.chb.2015.06.021

Lin, C., Griffiths, M. D., & Pakpour, A. H. (2018). Psychometric evaluation of Persian Nomophobia questionnaire: Differential item functioning and measurement invariance across gender. *Journal of Behavioral Addictions*, *7*(1), 100-108. doi:10.1556/2006.7.2018.11

Lopez-Fernandez, O., Kuss, D. J., Romo, L., Morvan, Y., Kern, L., Graziani, P., … Billieux, J. (2017). Self-reported dependence on mobile phones in young adults: A European cross-cultural empirical survey. *Journal of Behavioral Addictions*, *6*(2), 168-177. doi:10.1556/2006.6.2017.020

Lombardo, C. (2015). 18 Essential pros and cons of cell phones. Retrieved from https://greengarageblog.org/18-essential-pros-and-cons-of-cell-phones

Mail Online. (2008). Nomophobia is the fear of being out of mobile phone contact - and it's the plague of our 24/7 age. Retrieved from http://www.dailymail.co.uk/news/article-550610/Nomophobia-fear-mobile-phonecontact--Plague-24-7-age.html

Maquet, P., Laureys, S., Peigneux, P., Fuchs, S., Petiau, C., Phillips, C., … Cleeremans, A. (2000). Experience-dependent changes in cerebral activation during human REM sleep. *Nature Neuroscience*, *3*(8), 831-836. doi:10.1038/77744

Maree, T. (2017). The Social Media Use Integration Scale: Toward reliability and validity. *International Journal of Human–Computer Interaction*, *33*(12), 963-972. doi:10.1080/10447318.2017.1301041

Margin of error calculator. (n.d.). Retrieved from https://www.pollfish.com/margin-of-error-calculator/

Margolis, S., & Lyubomirsky, S. (2018). Cognitive outlooks and well-being. In E. Diener, S. Oishi, & L. Tay (Eds.), *Handbook of well-being*. Salt Lake City, UT: DEF Publishers. DOI:nobascholar.com

Maslow, A. H. (1987). *Motivation and personality (3rd ed.)*. Delhi, India: Pearson Education.

Maslow's Hierarchy of Needs. (2018). Retrieved from https://www.simplypsychology.org/maslow.html

Matar Boumosleh, J., & Jaalouk, D. (2017). Depression, anxiety, and smartphone addiction in university students- A cross sectional study. *PLOS ONE*, *12*(8), e0182239. doi:10.1371/journal.pone.0182239

McDonald, S. E. (2013). The effects and predictor value of in-class texting behavior on final course grades. *College Student Journal*, *47*(1), 34–40.

Melton, B. F., Bigham, L. E., Bland, H. W., Bird, M., & Fairman, C. (2014). Health-related Behaviors and Technology Usage among College Students. *American Journal of Health Behavior*, *38*(4), 510-518. doi:10.5993/ajhb.38.4.4

Mendoza, J. S., Pody, B. C., Lee, S., Kim, M., & McDonough, I. M. (2018). The effect of cellphones on attention and learning: The influences of time, distraction, and nomophobia. *Computers in Human Behavior*, *86*, 52-60. doi:10.1016/j.chb.2018.04.027

Moulin, K. L., & Chung, C. (2017). Technology trumping sleep: Impact of electronic media and sleep in late adolescent students. *Journal of Education and Learning, 6*(1), 294. doi:10.5539/jel.v6n1p294

Munezawa, T., Kaneita, Y., Osaki, Y., Kanda, H., Minowa, M., Suzuki, K., … Ohida, T. (2011). The association between use of mobile phones after lights out and sleep disturbances among Japanese adolescents: A nationwide cross-sectional survey. *Sleep*, *34*(8), 1013-1020. doi:10.5665/sleep.1152

Murdock, K. K., Adams, S. K., Crichlow-Ball, C., Horissian, M., & Roberts, M. (2019). Nighttime notifications and compulsivity illuminate the link between emerging adults' cellphone use and sleep-related problems. *Psychology of Popular Media Culture, 8*(1), 12-21. doi: 10.1037/ppm0000156

Murdock, K. K., Horissian, M., & Crichlow-Ball, C. (2017). Emerging adults' text message use and sleep characteristics: A multimethod, naturalistic study. *Behavioral Sleep Medicine, 15*(3), 228-241. doi:10.1080/15402002.2015.1120203

Ormrod, J. E. (2016). *Human Learning (7th ed.)*. New York, NY: Pearson.

Oswald, I. (1980). Sleep as a Restorative Process: Human Clues. *Progress in Brain Research*, 53, 279-288.

Pardun, C. J., L'Engle, K. L., & Brown, J. D. (2005). Linking exposure to outcomes: Early adolescents' consumption of sexual content in six media. *Mass Communication and Society, 8*(2), 75-91. doi:10.1207/s15327825mcs0802_1

Park, N., & Lee, H. (2012). Social implications of smartphone use: Korean college students' smartphone use and psychological well-being. *Cyberpsychology, Behavior, and Social Networking*, *15*(9), 491-497. doi:10.1089/cyber.2011.0580

Patterson, M. C. (2016). A naturalistic investigation of media multitasking while studying and the effects on exam performance. *Teaching of Psychology*, *44*(1), 51-57. doi:10.1177/0098628316677913

Perrin, A., & Jiang, J. (2018). A quarter of Americans are online almost constantly. Retrieved from http://www.pewresearch.org/fact-tank/2018/03/14/about-a-quarter-of-americans-report-going-online-almost-constantly/

Peterson, C., & Seligman, M. E. P. (2004). *Character strengths and virtues*. Oxford: Oxford University Press.

Pettijohn, T. F., Frazier, E., Rieser, E., Vaughn, N., & Hupp-Wilds, B. (2015). Classroom texting in college students. *College Student Journal, 49*(4), 513–516.

PEW Research Center, Internet & Technology: Mobile fact sheet. (2018). Retrieved from http://www.pewinternet.org/fact-sheet/mobile/

PEW Research Center, Internet & Technology: U.S. smartphone use in 2015. (2015, March 31). Retrieved from https://www.pewinternet.org/2015/04/01/us-smartphone-use-in-2015/pi_2015-04-01_smartphones_03/

PEW Research, Internet & Technology; Americans and their cell phones. (2011). Retrieved from http://www.pewinternet.org/2011/08/15/americans-and-their-cell-phones/

Principles for Constructing Web Surveys. (n.d.). Retrieved from https://www.scribd.com/document/252539567/Principles-for-Constructing-Web-Surveys

Redner, R., Lang, L. M., & Brandt, K. P. (2019). Evaluation of an electronics intervention on electronics use in a college classroom. *Behavior Analysis: Research and Practice*. doi:10.1037/bar0000158

Rosen, L. D., Carrier, M., & Cheever, N. A. (2013). Facebook and texting made me do it: Media-induced task-switching while studying. *Computers in Human Behavior, 29*, 948–958.

Rubinstein, J. S., Meyer, D. E., & Evans, J. E. (2001). Executive control of cognitive processes in task switching. *Journal of Experimental Psychology: Human Perception and Performance, 27*(4), 763-797.

Rules of thumb on magnitudes of effect sizes. (2019). Retrieved from https://imaging.mrc-cbu.cam.ac.uk/statswiki/FAQ/effectSize

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68–78.

Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual Review of Psychology, 52*, 141–166.

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality and Social Psychology, 57*, 1069–1081.

LaMotte, S. (2017). Smartphone addiction could be changing your brain. Retrieved from https://www.cnn.com/2017/11/30/health/smartphone-addiction-study/index.html

Şahin, C. (2018). Social Media Addiction Scale – Student Form: The reliability and validity study. *The Turkish Online Journal of Educational Technology, 17*(1), 169-182. doi:10.1037/t72756-000

SecurEnvoy. (2012). 66% of the population suffer from Nomophobia the fear of being without their phone. Retrieved from http://www.securenvoy.com/blog/2012/02/16/66-of-the-population-suffer-fromnomophobia-the-fear-of-being-without-their-phone/

Seligman, M. E. P. (2002). *Authentic happiness: Using the new positive psychology to realize your potential for lasting fulfillment*. New York: Free Press.

Shuttleworth, M. (n.d.). Face Validity. Retrieved from https://explorable.com/face-validity

Sleep disorders - Latest research and news | Nature. (2018). Retrieved from https://www.nature.com/subjects/sleep-disorders

Słojewski, M. (2013). Cell phones give more benefits than risks, but... *Central European Journal of Urology, 65*, 54-55. doi:10.5173/ceju.2013.01.art17

Smith, A., Raine, L., & Zickuhr, K. (2011). College students and technology (The Pew Research Center's Internet and American Life Project). Retrieved from http://www.pewinternet.org/2011/07/19/college-students-and-technology/

Smith, A. (2015). U.S. smartphone use in 2015. Retrieved from https://www.pewinternet.org/2015/04/01/us-smartphone-use-in-2015/

Sticca, F., Goetz, T., Bieg, M., Hall, N. C., Eberle, F., & Haag, L. (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), e0187367. doi:10.1371/journal.pone.0187367

Student data and reports. (n.d.). Retrieved March 30, 2020, from https://dars.tamu.edu/Student/Preliminary-Enrollment-(1)?_ga=2.152189049.1917902325.1585590429-1828266557.1558703200

Tao, S., Wu, X., Zhang, Y., Zhang, S., Tong, S., & Tao, F. (2017). Effects of sleep quality on the association between problematic mobile phone use and mental health symptoms in chinese college students. *International Journal of Environmental Research and Public Health*, *14*(2), 185. doi:10.3390/ijerph14020185

Teaching and learning after COVID-19. (2020, April 1). Retrieved from https://www.insidehighered.com/digital-learning/blogs/learning-innovation/teaching-and-learning-after-covid-19

Telef, B. B. (2013). The adaptation of psychological well-being into Turkish: A validity and reliability study [in Turkish]. *Hacettepe Üniversitesi Eğitim Fakültesi Dergisi [Hacettepe University Journal of Education], 28*(3), 374- 384.

The Internet World Stats. (2016). Mobile internet – mobile phones and smart mobile phones. Retrieved from http://www.internetworldstats.com/mobile.htm

The national campaign to prevent teen and unplanned pregnancy and cosmogirl.com. Sex and tech: results from a survey of teens and young adults. (n.d.). Retrieved from https://powertodecide.org/sites/default/files/resources/primary-download/sex-and-tech.pdf

Thomée, S., Eklöf, M., Gustafsson, E., Nilsson, R., & Hagberg, M. (2007). Prevalence of perceived stress, symptoms of depression and sleep disturbances in relation to information and communication technology (ICT) use among young adults – an explorative prospective study. *Computers in Human Behavior*, *23*(3), 1300-1321. doi:10.1016/j.chb.2004.12.007

Thomée, S., Dellve, L., Härenstam, A., & Hagberg, M. (2010). Perceived connections between information and communication technology use and mental symptoms among young adults - a qualitative study. *BMC Public Health*, *10*(1). doi:10.1186/1471-2458-10-66

Thomée, S., Härenstam, A., & Hagberg, M. (2011). Mobile phone use and stress, sleep disturbances, and symptoms of depression among young adults - a prospective cohort study. *BMC Public Health*, *11*(1). doi:10.1186/1471-2458-11-66

Tindell, D. R., & Bohlander, R. W. (2012). The use and abuse of cell phones and text messaging in the classroom: A survey of college students. *College Teaching, 60*(1), 1–9. doi:10.1080/87567555.2011.604802

Tosini, G., Ferguson, I, & Tsubota, K. (2016). Effects of blue light on the circadian system and eye psychology. *Molecular Vision*, *22*, 61-72.

Tossell, C. C., Kortum, P., Shepard, C., Rahmati, A., & Zhong, L. (2015). You can lead a horse to water but you cannot make him learn: Smartphone use in higher education. *British Journal of Educational Technology*, *46*(4), 713–724. doi:10.1111/bjet.12176

Towne, S. D., Ory, M. G., Smith, M. L., Peres, S. C., Pickens, A. W., Mehta, R. K., & Benden, M. (2017). Accessing physical activity among young adults attending a university: the role of sex, race/ethnicity, technology use, and sleep. *BMC Public Health*, *17*(1). doi:10.1186/s12889-017-4757-y

U.S. Census Bureau QuickFacts: United States. (n.d.). Retrieved April 9, 2020, from https://www.census.gov/quickfacts/fact/table/US/RHI125218#RHI125218

U.S. smartphone users statistics in 2017: a 'Round-the-Clock' connection. (2017). Retrieved from https://www.reportlinker.com/insight/smartphone-connection.html

Van den Bulck, J. (2004). Television viewing, computer game playing, and Internet use and self-reported time to bed and time out of bed in secondary-school children. *Sleep*, *27*(1), 101-104. doi:10.1093/sleep/27.1.101

Van der Molen, J. H., & Bushman, B. J. (2008). Children's Direct Fright and Worry Reactions to Violence in Fiction and News Television Programs. *The Journal of Pediatrics, 153*(3), 420-424. doi:10.1016/j.jpeds.2008.03.036

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes* Cambridge, Mass.: Harvard University Press.

Wade, J. (2017). The advantages of teenagers having mobile phones. Retrieved from https://howtoadult.com/the-advantages-of-teenagers-having-mobile-phones-12944089.html

Weaver, E., Gradisar, M., Dohnt, H., Lovato, N., & Douglas, P. (2010). The effect of presleep video-game playing on adolescent sleep. *Journal of Clinical Sleep Medicine, 6*(2), 184–189.

Which generation is most distracted by their phones? (2016). Retrieved from https://priceonomics.com/which-generation-is-most-distracted-by-their/

Williams, D. (2006). On and off the 'net: Scales for social capital in an online era. *Journal of Computer-Mediated Communication, 11*, 593-628.

Winnick, M. (2016, June 16). Putting a finger on our phone obsession. Retrieved from https://blog.dscout.com/mobile-touches

Wood, J. (2018). College students in study spend 8 to 10 hours daily on cell phone. Retrieved from https://psychcentral.com/news/2014/08/31/new-study-finds-cell-phone-addiction-increasingly-realistic-possibility/74312.html

Wood, E., Zivcakova, L., Gentile, P., Archer, K., De Pasquale, D., & Nosko, A. (2012). Examining the impact of off-task multi-tasking with technology on real-time classroom learning. *Computers & Education*, *58*, 365–374.

Wood, B., Rea, M. S., Plitnick, B., & Figueiro, M. G. (2013). Light level and duration of exposure determine the impact of self-luminous tablets on melatonin suppression. *Applied Ergonomics, 44*(2), 237-240. doi:10.1016/j.apergo.2012.07.008

World Health Organization [WHO]. (2015). Public health implications of excessive use of the internet, computers, smartphones and similar electronic devices: Meeting report, Main Meeting Hall, Foundation for Promotion of Cancer Research, National Cancer Research Centre, Tokyo, Japan, 27–29 August 2014. Geneva, Switzerland: WHO. Retrieved from http://www.who.int/iris/handle/10665/184264#sthash.iy5Vm60q.dpuf

Xu, F., Adams, S. K., Cohen, S. A., Earp, J. E., & Greaney, M. L. (2019). Relationship between physical activity, screen time, and sleep quantity and quality in US adolescents aged 16–19. *International Journal of Environmental Research and Public Health*, *16*(9), 1524. doi:10.3390/ijerph16091524

Ya'u, L., & Idris, B. (2015). Theory of planned behaviour and the use of cell/mobile phone in the classroom. *International Research Journal of Electronics and Computer Engineering*, *1*(1), 1. doi:10.24178/irjece.2015.1.1.01

Yot-Domínguez, C., & Marcelo, C. (2017). University students' self-regulated learning using digital technologies. *International Journal of Educational Technology in Higher Education*, *14*(38). doi:10.1186/s41239-017-0076-8

Zarghami, M., Khalilian, A., Setareh, J., & Salehpour, G. (2015). The impact of using cell phones after light-out on sleep quality, headache, tiredness, and distractibility among students of a university in north of Iran. *Iranian Journal of Psychiatry and Behavioral Sciences*, *9*(4). doi:10.17795/ijpbs-2010

Zimmerman, B. J. (1986). Becoming a self-regulated learner: which are the key subprocesses?. *Contemporary Educational Psychology*, *11*, 307–313. doi: 10.1016/0361-476x(86)90027-5

Zimmerman, B. J., & Martinez-Pons, M. (1986). Development of a structured interview for assessing student use of self-regulated learning strategies. *American Educational Research Journal*, 23, 614 - 628.

Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology*, *81*, 329–339. doi: 10.1037/0022-0663.81.3.329

Zimmerman, B. J., Bandura, A., & Martinez-Pons, M. (1992). Self-Motivation for Academic Attainment: The Role of Self-Efficacy Beliefs and Personal Goal Setting. *American Educational Research Journal*, *29*(3), 663. doi:10.2307/1163261

Zimmerman, B. J. (2000). "Attaining self-regulation: a social cognitive perspective," in *Handbook of Self-Regulation*, eds M. Boekaerts, P. R. Pintrich, and M. Zeidner

(San Diego, CA: Academic Press), 13–40. doi: 10.1016/b978-012109890-2/50031-7

Zimmerman, B. J., & Moylan, A. R. (2009). "Self-regulation: where metacognition and motivation intersect," in *Handbook of Metacognition in Education*, eds D. J. Hacker, J. Dunlosky, and A. C. Graesser (New York, NY: Routledge), 299–315.

APPENDIX A

INVITATION EMAIL

Subject: Participants needed for a Cell Phone Use study.

from: scjoshidat2012@tamu.edu

reply-to: scjoshidat2012@tamu.edu

date:

Are you an Undergraduate student (in any class level and from any major at Texas A&M) who own/use a cell phone (i. e. mobile phone, smartphone)?

This study may help you inform and regulate your cell phone habits!

This study is intended to investigate the impact of cell phone use on sleep quality, academic performance and psychological well-being of young adults. Your responses will contribute to the diverse data bank of my dissertation. The survey should take 20 – 30 minutes to complete. It is highly recommended to complete it in one sitting. Partially completed responses will be removed from the study, as these might not qualify as completed.

As being a participant of this study, you will have an opportunity to enter in a drawing and will have the chance to win two tickets for November 02, 2019 Texas A&M football game (UTSA vs. Texas A&M).

Here is the survey link

(https://tamucehd.qualtrics.com/jfe/form/SV_beZQlIAeDGTqbOJ).

Have questions? Email me at scjoshidat2012@tamu.edu

I appreciate your time.

Suresh Joshi

Doctoral student

Educational Psychology

Texas A&M University

(313)652-6373

TAMU IRB # IRB2019-0980M

Approved: August 23, 2019

Expiration Date: August 23, 2022

APPENDIX B

INFORMED CONSENT

All enrolled undergraduate students (at the time of taking this survey) at Texas A&M University (TAMU) are invited to participate in this study that is being conducted by Suresh Joshi, a doctoral student in the Department of Educational Psychology, TAMU. The information in this form will cover all aspects of the study and will help study participants understand their rights/benefits as a participant. Upon agreeing to participate, students will not give up any of their legal rights and will have the right to drop from the study at any point of time without penalty.

Title of the Study: Investigating Young Adult Cell Phone Use: Implications for Sleep Quality, Academic Performance, and Psychological Well-Being

Why Is This Study Being Done? The purpose of this study is to investigate the impact of cell phone use on sleep quality, academic performance and psychological well-being of the young adults.

Why Am I Being Asked to Be in This Study? Because you are an undergraduate student who is enrolled in a course at TAMU.

How Many People Will Be Asked to Be in This Study? All undergraduate students enrolled at TAMU.

What Will I Be Asked to Do in This Study? To complete an online survey that may take 20 – 30 minutes (approx.) of your time.

Are There Any Risks to Me? The things that you will be doing carry no more risks than you would come across in everyday life. Although the researchers have tried to avoid risks, you may feel that some questions/procedures that are asked of you might be stressful or upsetting. Information about individuals and/or organizations that may be able to help you with these problems will be given to you.

Are There Any Benefits to Me? There are no direct benefits for participating in this research.

Will There Be Any Costs to Me? Aside from your time, no cost is involved in participating in the study.

Will I Be Paid to Be in This Study? You will have an opportunity to enter in a drawing and will have the chance to win two tickets for November 02, 2019 Texas A&M football game (UTSA vs. Texas A&M).

Will Information from This Study Be Kept Confidential? The records of this study will be kept strictly confidential. No identifiers linking you to this study will be included in any sort of report that might be published. Research records will be stored securely and only the researchers will have access to the records. Study data will be stored in computer files protected with a password. This consent form will also be filed securely in an official area.

People who have access to your information include the Principal Investigators and the study personnel. Representatives of regulatory agencies such as the Office of Human Research Protections (OHRP) and entities such as the Texas A&M University Human Subjects Protection Program may access your records to make sure the study is being run correctly and that information is collected properly. Furthermore, all information related to this study will be kept confidential to the extent permitted or required by the law.

Who may I Contact for More Information? You may contact Suresh Joshi to inform about any questions or concerns regarding this study at 313-652-6373 or email him at scjoshidat2012@tamu.edu. For questions about your rights as a research participant, to provide input regarding research, or if you have questions, complaints, or concerns about the research, you may call the Texas A&M University Human Subjects Protection Program office by phone at 1-979-458-4067, toll-free at 1-855-795-8636, or by email at irb@tamu.edu.

What if I Change My Mind About Participating? Your participation in this study is completely voluntary, and you have the choice whether or not to participate. Moreover, you may decide to not to begin or to stop participating at any time during the study. The participation in this study or not participating in the study will have no effect on your student status and relationship with Texas A&M University. Any new information discovered about the research will be provided to you.

Please go ahead and hit the "**I Agree**" button if you decide to participate in the study.

STATEMENT OF CONSENT

I agree to be in this study and know that I am not giving up any legal rights by signing this form. The procedures, risks, and benefits have been explained to me, and my questions have been answered. I can ask more questions if I want.

APPENDIX C

STUDY INSTRUMENT

Demographic information:

1. **Sex** Male Female Intersex Prefer not to answer

2. **Ethnicity** African American Caucasian Asian Latinx

Native American Native Islander Prefer not to answer

3. **Age** Click to write (18 - 60) …………..

4. **Email** (If you would like to participate in the drawing to win TAMU game tickets) …..

5. **How many years have you attended (in person) a two year or four year higher-institution?**

1. Starting first year - incoming freshman
2. Starting second year - sophomore
3. Starting third year - junior
4. Starting fourth year - senior
5. Starting fifth year (or beyond) - returning senior

6. **Declared Major:____________________________**

7. **High School Grade Point Average** (slide to the appropriate number … a 5-point scale is provided, but if your high school used a 4-point scale, please indicate that number)

8. Current Collegiate Grade Point Average (slide to the appropriate number)

The next set of questions relate to your recent cell phone use habits (CPU Instrument)

9. CPU_Total:

As accurately as possible, please estimate **the total amount of time you spend** using your cell phone **per day** on each of the following uses

*Note … all times listed in hours, but you can estimate minutes using the sliding scale. (EX: 30 minutes = .5 hours).

Calling	0 to 12 hrs.
Texting	0 to 12 hrs.
Taking photos or recording videos	0 to 12 hrs.
Listening to Podcasts	0 to 12 hrs.
Watching Videos (Netflix, Hulu, etc.)	0 to 12 hrs.
Gaming	0 to 12 hrs.
Non Social Media Internet Browsing (Shopping, surfing, etc.)	0 to 12 hrs.
Social Media (Instagram, Twitter, Snapchat, Facebook, etc.)	0 to 12 hrs.
Email (sending and receiving)	0 to 12 hrs.
Other app or software driven use not listed above	0 to 12 hrs.

Total hours (Please note that the total number of hours cannot exceed the number of hours in a day and night cycle): ________________________

10. CPU_Nighttime: These items are intended to assess participants' nighttime cell phone use during the past month.

(i) **CPU_BeforeBed:** To accurately gauge cell phone use at night during the past month, please answer the following questions. For the purpose of answering, target bedtime reflects the hour that you INTENDED to go to sleep.

*(*Note: For this question, Never/Rarely = Not even once/only when required; Occasionally = Infrequently but not compulsively; Often = Regularly but not constantly; Always = Constantly)*

(i) In the last 30 days, have you been awakened by cell phone calls after going to bed at night?

Never Occasionally Often Always

(ii) In the last 30 days, have you been awakened by cell phone texts after going to bed at night?

Never Occasionally Often Always

(iii) In the last 30 days, have you been awakened by cell phone notifications after going to bed at night?

Never Occasionally Often Always

(iv) In the last 30 days, have you stayed up late to use your cell phone for calling after a target bedtime?

Never Occasionally Often Always

(v) In the last 30 days, have you stayed up late to use your cell phone for texting (sending or receiving) after a target bedtime?

Never Occasionally Often Always

(vi) In the last 30 days, have you stayed up late to use your cell phone for emailing (receiving, writing, sending) after a target bedtime?

Never Occasionally Often Always

(vii) In the last 30 days, have you stayed up late to use your cell phone for listening to Podcasts or listening to music after going to bed at night?

Never Occasionally Often Always

(viii) In the last 30 days, have you stayed up late to use your cell phone for social media (Instagram, Twitter, Snapchat, Facebook, LinkedIn, etc.) activities after a target bedtime?

Never Occasionally Often Always

(ix) In the last 30 days, have you stayed up late to use your cell phone for watching videos (Netflix, Hulu, etc.), gaming, non social media internet browsing (Shopping, surfing, etc.), and all other uses, driven by apps and software after going to bed at night?

Never Occasionally Often Always

(ii) CPU_Arousal:

(i) In the last 30 days, how common is it for you to use your cell phone to engage in the following activities before or after going to bed at night:

(1 = not common at all / 10 = extremely common)

(a) emotionally charged text messages and images

1 2 3 4 5 6 7 8 9 10

(b) explicit content pertaining to sexuality (pornography, tinder, dating sites, etc.)

1 2 3 4 5 6 7 8 9 10

(c) explicit content pertaining to violence (video games, movies, etc.)

1 2 3 4 5 6 7 8 9 10

(ii) In the last 30 days, rate how common it is for you to be kept awake by engaging in the following cell phone activities OR by thinking about occurrences earlier in the day

(1 = not common at all / 10 = extremely common)

(a) Reading or responding to emotionally charged text messages and images

1 2 3 4 5 6 7 8 9 10

(b) Sexually-oriented apps, multimedia, or related materials

1 2 3 4 5 6 7 8 9 10

(c) Violence-based apps, games, multimedia, or related materials

1 2 3 4 5 6 7 8 9 10

11. CPU_Academic

(i) CPU_Classroom (CPU_Switch):

During a 60-minute class/lecture, lab, and/or study session, how often do you switch to

(i) check your cell phone for text messages (including instant messages) and read them

0 times ……………………………………………..………….40 times

(ii) use your cell phone to write a reply to a text message

0 times ……………………………………………..………….40 times

(iii) check your cell phone for commercial notifications such as promotional offers (shopping, banking, etc.)

0 times ……………………………………………...………….40 times

(iv) respond to commercial notifications such as promotional offers (shopping, banking, etc.) using your cell phone

0 times ……………………………………………...………….40 times

(v) check your cell phone for social media (Instagram, Twitter, Snapchat, Facebook, LinkedIn, etc.) notifications

0 times ……………………………………………...………….40 times

(vi) use your cell phone to write (or to respond to) messages on social media (Instagram, Twitter, Snapchat, Facebook, LinkedIn, etc.)

0 times ……………………………………………...………….40 times

(vii) check your emails using your cell phone

0 times ……………………………………………...………….40 times

(viii) use your cell phone to write (or to respond to) emails

0 times ……………………………………………...………….40 times

(ix) check your cell phone for any type of reminders (calendar, meeting alerts, alarms, timers etc.)

0 times ……………………………………………...………….40 times

(x) use your cell phone for surfing the Internet (for academic or non-academic purposes)

0 times ……………………………………………...………….40 times

(ii) **CPU_SRLBehaviour:** On a daily basis, how often do you use your cell phone to

(i) use an alarm to regulate sleeping/waking-up

Never Occasionally Often Always

(ii) use a calendar to indicate important dates, set goals, or keep a schedule

Never Occasionally Often Always

(iii) use notes to write strategies, monitor progress, or evaluate yourself

Never Occasionally Often Always

(iv) use a timer, stopwatch, or clock function to adhere to a study schedule

Never Occasionally Often Always

(v) use a search engine or another learning tool to obtain course information (Google search, eCampus, BlackBoard etc.)

Never Occasionally Often Always

(vi) use Google Docs, etc. to review, rehearse, or revise class notes

Never Occasionally Often Always

(vii) use email or social media to seek peer, teacher, or any other academic assistance

Never Occasionally Often Always

(viii) use text messaging to clarify information, collaborate with peers, or get quick answers

Never Occasionally Often Always

(ix) use a calculator to complete mathematical functions related to an assignment

Never Occasionally Often Always

12. CPU_SocialMedia

(i) CPU_SocialMediaFeeling: From a social media standpoint (Instagram, Twitter, Facebook, Snapchat, LinkedIn, etc.), relate how your cell phone makes you feel along the following dimensions

(i) Social media apps make me feel engaged and connected to my peers

Never Occasionally Often Always

(ii) I find social media apps interesting and it satisfies a curiosity

Never Occasionally Often Always

(iii) I feel pleasure and a sense of enjoyment when I use social media apps

Never Occasionally Often Always

(iv) I find social media apps meaningful and a good use of my time

Never Occasionally Often Always

(v) I feel a great sense of purpose and fulfillment when I use social media

Never Occasionally Often Always

(vi) Using social media apps makes me feel optimistic about myself and my future

Never Occasionally Often Always

(vii) Social media apps give me a sense of belonging and acceptance

Never Occasionally Often Always

(viii) Through social media, I feel competent and accomplished in activities that I feel are important to me

Never Occasionally Often Always

14. CPU_SMResponse: Based on your engagement with social media apps (Instagram, Twitter, Facebook, Snapchat, LinkedIn, etc.), rate how well the following statements apply to you:

*Note: A response on social media may include, but not limited to, commenting, liking, sharing, loving, using emojis, posting GIF's, attaching stickers, etc.

(i) feel like I'm connected to my friends when I actively respond to OTHERS posts on social media

Never Occasionally Often Always

(ii) feel like I contribute to the well-being of others when I actively respond to OTHERS posts on social media

Never Occasionally Often Always

(iii) feel liked when others respond to YOUR posts on social media

Never Occasionally Often Always

(iv) feel rewarded when you respond to OTHERS posts on social media

Never Occasionally Often Always

The next set of questions relate to your psychological well-being

Below are eight statements with which you may agree or disagree. Using the scale below, indicate your agreement with each item by placing the appropriate number on the line preceding that item. Please be open and honest in your response

Strongly agree (5) Agree (4) Neither agree nor disagree (3)

Disagree (2) Strongly disagree (1)

1. I lead a purposeful and meaningful life

2. My social relationships are supportive and rewarding

3. I am engaged and interested in my daily activities

4. I actively contribute to the happiness and well-being of others

5. I am competent and capable in the activities that are important to me.

6. I am a good person and live a good life

7. I am optimistic about my future

8. People respect me

The next set of questions relate to your sleep habits

The following questions relate to your usual sleep habits during the past month *only*. Your answers should indicate the most accurate reply for the *majority* of days and nights in the past month. Please answer all the questions.

1. During the past month, when have you usually gone to bed at night?

   usual bed time____

2. During the past month, how long (in minutes) has it usually taken you to fall asleep each night?

   number of minutes______________________________________

3. During the past month, when have you usually got up in the morning?

   usual getting up time___________________________________

4. During the past month, how many hours of *actual* sleep did you get at night? (This may be different than the number of hours you spend in bed) bed).

   hours of sleep per night_________________________________

5. For each of the remaining questions, check the one best response. Please answer *all* Questions.

During the past month, how often have you had trouble sleeping because you……

(a) Cannot get to sleep within 30 minutes

Not during the past month____	Less than once a week_____	Once or twice a week___	three or more times a week

(b) Wake up in the middle of the night or early morning

Not during the past month____	Less than once a week_____	Once or twice a week___	three or more times a week

(c) Have to get up to use the bathroom

Not during the past month____	Less than once a week_____	Once or twice a week___	three or more times a week

(d) Cannot breathe comfortably

Not during the past month____	Less than once a week_____	Once or twice a week___	three or more times a week

(e) Cough or snore loudly

Not during the past month____	Less than once a week_____	Once or twice a week___	three or more times a week

(f) Feel too cold

Not during the past month____	Less than once a week_____	Once or twice a week___	three or more times a week

(g) Feel too hot

Not during the	Less than	Once or	three or more
past month____	once a week_____	twice a week___	times a week

(h) Had bad dreams

Not during the	Less than	Once or	three or more
past month____	once a week_____	twice a week___	times a week

(i) Have pain

Not during the	Less than	Once or	three or more
past month____	once a week_____	twice a week___	times a week

(j) Other reason(s), please describe ______________________________

How often during the past month have you had trouble sleeping because of this?

Not during the	Less than	Once or	three or more
past month____	once a week_____	twice a week___	times a week

6. During the past month, how would you rate your sleep quality overall?

Very good____Fairly good___Fairly bad____Very bad_____

7. During the past month, how often have you taken medicine (prescribed or “over the counter”) to help you sleep?

Not during the	Less than	Once or	three or more
past month____	once a week_____	twice a week___	times a week

8. During the past month, how often have you had trouble staying awake while driving, eating meals, or engaging in social activity?

Not during the past month____	Less than once a week_____	Once or twice a week___	three or more times a week

9. During the past month, how much of a problem has it been for you to keep up enough enthusiasm to get things done?

No problem at all___Only a very slight problem_Somewhat of a problem___A very big problem____

10. Do you have a bed partner or roommate?

No bed partner or roommate__Partner/roommate in other room___Partner in same room, but not same bed_Partner in same bed__

If you have a roommate or bed partner, ask him/her how often in the past month you have had…

(a) Loud snoring

Not during the past month …….. Less than Once a week ……… Once or twice a week ………. Three or more times a week ………….

(b) Long pauses between breaths while asleep

Not during the past month …….. Less than Once a week ……… Once or twice a week ………. Three or more times a week ………….

(c) Legs twitching or jerking while you sleep

Not during the past month …….. Less than Once a week ……… Once or twice a week ………. Three or more times a week ………….

(d) Episodes of disorientation or confusion during sleep

Not during the past month ……... Less than Once a week ……… Once or twice a week ………. Three or more times a week ………….

(e) Other restlessness while you sleep: please describe --------------------------------

How often during the past month have you had trouble sleeping because of this?

Not during the past month ……... Less than Once a week ……… Once or twice a week ………. Three or more times a week ………….

APPENDIX D

APPROVAL FROM INSTITUTIONAL REVIEW BOARD, TEXAS A&M

DIVISION OF RESEARCH

TEXAS A&M UNIVERSITY

EXEMPTION DETERMINATION

(Common Rule –Effective January, 2018)

August 23, 2019

Type of Review:	Initial Review Submission Form
Title:	"Investigating Young Adult Cell Phone Use: Implications for Sleep Quality, Academic Performance, and Psychological Well-Being"
Investigator:	Steven Woltering
IRB ID:	IRB2019-0980M
Reference Number:	081383
Funding:	Internal Funds
Documents Reviewed:	*Informed consent latest 1.0* *Dissertation proposal latest 2.1* *Recruitment email 1.0* *Sleep study Instrument scj 1.0*
Review Category	Category 2: Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met: i. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects; ii. Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation; or iii. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects can readily be ascertained, directly or through identifiers linked to the subjects, and an IRB conducts a limited IRB review to make the determination required by .111(a)(7).

Dear Steven Woltering:

The HRPP determined on 08/23/2019 that this research meets the criteria for Exemption in accordance with 45 CFR 46.104.

750 Agronomy Road, Suite 2701
1186 TAMU
College Station, TX 77843-1186

Tel. 979.458.1467 Fax. 979.862.3176
http://rcb.tamu.edu

This determination applies only to the activities described in this IRB submission and does not apply should any changes be made. If changes are made you must immediately contact the IRB. You may be required to submit a new request to the IRB.

Your exemption is good for three (3) years from the Approval Start Date. Thirty days prior to that time, you will be sent an Administrative Check-In Notice to provide an update on the status of your study.

If you have any questions, please contact the IRB Administrative Office at 1-979-458-4067, toll free at 1-855-795-8636.

Sincerely,
IRB Administration

APPENDIX E

PRINCIPAL COMPONENT FACTOR ANALYSIS

Table E.1 shows the Kaiser-Meyer-Olkin (KMO) measures of sampling adequacy for the constructs of CPU_BeforeBed, CPU_Arousal, CPU_Switch, CPU_SRLBehavior, CPU_SMFeeling, and CPU_SMResponse. A statistically significant KMO above 0.5 indicates that each item loads well on a designated construct. Greater KMO (> 0.5) specifies better loading. The KMO's for all six constructs were statistically significant ($p < 0.001$). All nine items from the construct of CPU_BeforeBed (KMO = 0.79, $p < 0.001$) and all six items from the construct of CPU_Arousal (KMO = 0.59, $p < 0.001$) loaded well within the constructs. All ten items from the construct of CPU_Switch (KMO = 0.89, $p < 0.001$) and all nine items from the construct of CPU_SRLBehavior (KMO = 0.78, $p < 0.001$) also loaded well within these constructs. In addition, all eight items from the construct of CPU_SMFeeling (KMO = 0.89, $p < 0.001$) and all four items from the construct of CPU_SMResponse (KMO = 0.72, $p < 0.001$) loaded well within these constructs.

Table E.1

Kaiser-Meyer-Olkin Measure of Sampling Adequacy for CPU_BeforeBed, CPU_Arousal, CPU_Switch, CPU_SRL, CPU_SMF, and CPU_SMR

Variable	Kaiser-Meyer-Olkin Measure of Sampling Adequacy
CPU_BeforeBed	0.79*
CPU_Arousal	0.59*
CPU_Switch	0.89*
CPU_SRLBehavior	0.78*
CPU_SMF	0.89*
CPU_SMR	0.82*

Note. CPU_Total = Total hours-per-day spent using cell phones, CPU_BeforeBed = The use of cell phone before sleep, CPU_Arousal = The use of cell phones for accessing sexually explicit, violently, or emotionally charged media content, CPU_Switch = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRL = The use of cell phones for self-regulated learning strategies, CPU_SMF = Cell phone social media feeling, CPU_SMR = Cell phone social media response.

*$p < 0.001$.

APPENDIX F

CHARACTERISTICS OF VARIABLES

Table F.1

The Characteristics of the Variables and Statistical Analyses Used for Cell Phone Use Study

Variables		Variable Type	Correlation	Regression
Independent				
	CPU_Total	Continuous (ratio)	N/A	Ordinal logistic
	CPU_BeforeBed	Continuous (ordinal, ranked)	N/A	Ordinal logistic
	CPU_Arousal	Continuous (ordinal, ranked)	N/A	Ordinal logistic
	CPU_Switch	Continuous (ratio)	Spearman (non-normal, skewed)	Linear
	CPU_SRL	Continuous (ordinal)	Spearman (non-normal, skewed)	Linear
	CPU_SMF	Continuous (ordinal, ranked) (Likert Scale)	Spearman (non-normal, skewed)	Ordinal logistic
	CPU_SMR	Continuous (ordinal, ranked) (Likert Scale)	Spearman (non-normal, skewed)	Ordinal logistic
Dependent				
	Sleep latency	Categorical (ordinal)	N/A	Ordinal logistic
	Sleep difficulty	Categorical (ordinal)	N/A	Ordinal logistic
	GPA	Continuous (interval)	Spearman (non-normal, skewed)	Linear (Homoscedastic)

PWB	Continuous (ordinal)	Spearman (non-normal, skewed)	Ordinal logistic (Heteroscedastic)

Note. CPU_Total = Total hours-per-day spent using cell phones, CPU_BeforeBed = The use of cell phone before sleep, CPU_Arousal = The use of cell phones for accessing sexually explicit, violently, or emotionally charged media content, CPU_Switch = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRL = The use of cell phones for self-regulated learning strategies, CPU_SMF = Cell phone social media feeling, CPU_SMR = Cell phone social media response, GPA – Grade point average, PWB – Psychological well-being.

APPENDIX G

MISSING DATA CASE PROCESSING SUMMARY

Table G.1

Missing Data Case Processing Summary for CPU_Total, CPU_BeforeBed, CPU_Arousal, CPU_Switch, CPU_SRL, CPU_SMF, CPU_SMR, Sleep Latency, Sleep difficulty, Grade Point Average (GPA), and Psychological well-being (PWB) (N = 525)

	Cases			
	Valid		Missing	
	N	Percent	N	Percent
CPU_Total	525	100.0%	0	0.0%
CPU_BeforeBed	525	100.0%	0	0.0%
CPU_Arousal	525	100.0%	0	0.0%
CPU_Switch	525	100.0%	0	0.0%
CPU_SRL	525	100.0%	0	0.0%
CPU_SMF	525	100.0%	0	0.0%
CPU_SMR	525	100.0%	0	0.0%
Sleep Latency	525	100.0%	0	0.0%
Sleep Difficulty	525	100.0%	0	0.0%
GPA	525	100.0%	0	0.0%
PWB	525	100.0%	0	0.0%

Note. CPU_Total = Total hours-per-day spent using cell phones, CPU_BeforeBed = The use of cell phone before sleep, CPU_Arousal = The use of cell phones for accessing sexually explicit, violently, or emotionally charged media content, CPU_Switch = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRL =

The use of cell phones for self-regulated learning strategies, CPU_SMF = Cell phone social media feeling, CPU_SMR = Cell phone social media response.

APPENDIX H

CONTROL ANALYSIS

Ceiling Effect and Floor Effect for Test-Items

No ceiling or floor effect was found because the frequency percentage of respondents achieving the lowest or highest possible score was less than 15% for all predicting variables. The frequency percentage of predicting variables was as follows: CPU_BeforeBed (for lowest score - 0.8%, for highest score - 0.2%), CPU_Arousal (for lowest score - 9.5%, for highest score - 0.2%), CPU_Switch (for lowest score - 2.1%, for highest score - 0.2%), CPU_SRLBehavior (for lowest score - 0.6%, for highest score - 4.0%), CPU_SMFeeling (for lowest score - 3.4%, for highest score - 1.1%), and CPU_SMResponse (for lowest score - 6.1%, for highest score - 6.1%).

Test of Skewness and Kurtosis

Table H.1

Skewness and Kurtosis for Grade Point Average (GPA), and Psychological well-being (PWB)

	N	Skewness	Kurtosis
GPA	524	-0.505	-0.059
PWB	520	-0.458	-0.003

Test of Homoscedasticity

The scatterplot of GPA (Fig. 2) showed that the data points were approximately at the same distance from the regression line throughout the dataset, therefore, was homoscedastic in nature. The scatterplot of PWB (Fig. 3) showed that the data points were at widely varying distances from the regression line throughout the dataset, therefore, was hetroscedastic in nature.

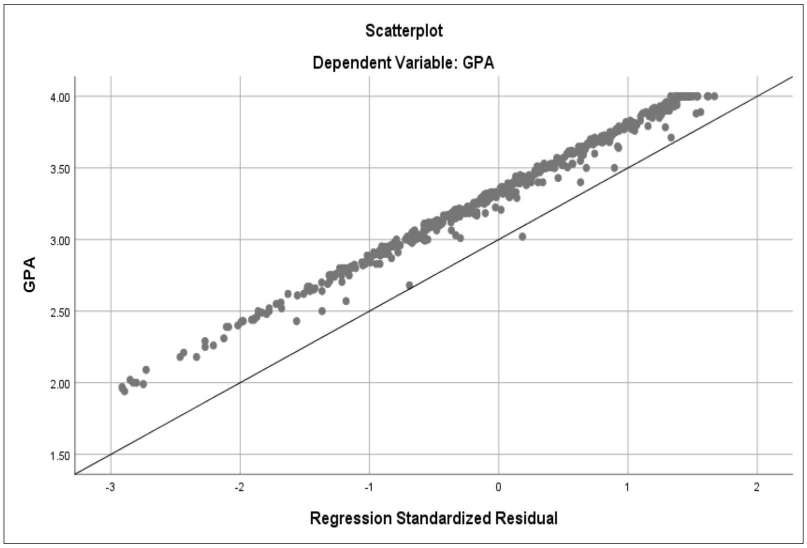

Figure 2. Scatterplot for GPA

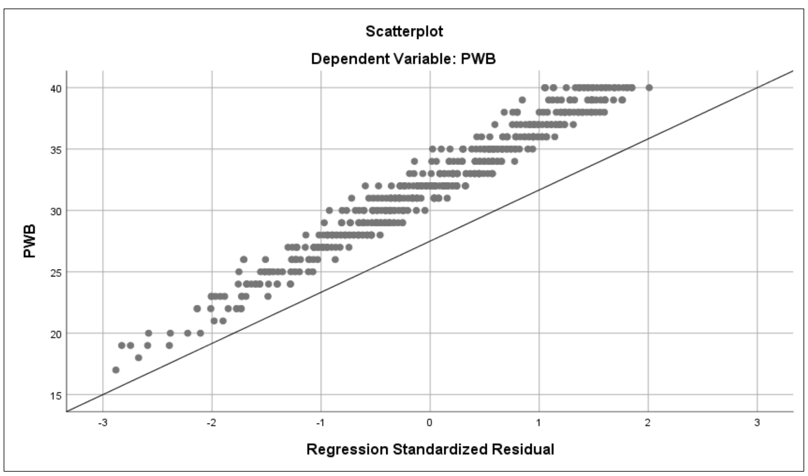

Figure 3. Scatterplot for Psychological Well-Being

Test of Collinearity

None of the predictors in our study (CPU_Total, CPU_BeforeBed, CPU_Arousal, CPU_Switch, CPU_SRL, CPU_SMF, and CPU_SMR) were correlated with other variables because the variance inflation factor (VIF) for all the predictors was less than 3 (Table 12). The predictors with VIF more than 4 probably have multicollinaerity and warrant further investigation, and the predictors with VIF more than 10 definitely have multicollinearity issues requirring corrections ("Detecting Multicollinearity using variance inflation factors," n.d.).

Table H.2

Test of Collinearity for Age, CPU_Total, CPU_BeforeBed, CPU_Arousal, CPU_Switch, CPU_SRL, CPU_SMF, and CPU_SMR (N = 525)

	Collinearity Statistics	
Model/Variable	Tolerance	VIF
Age	0.968	1.033
CPU_Total	0.937	1.068
CPU_BeforeBed	0.705	1.419
CPU_Arousal	0.760	1.315
CPU_Switch	0.769	1.301
CPU_SRL	0.841	1.190
CPU_SMF	0.538	1.859
CPU_SMR	0.546	1.831

Note. Dependent Variables = Grade point average and psychological well-being. CPU_Total = Total hours-per-day spent using cell phones, CPU_BeforeBed = The use of cell phone before sleep, CPU_Arousal = The use of cell phones for accessing sexually explicit, violently, or emotionally charged media content, CPU_Switch = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRL

= The use of cell phones for self-regulated learning strategies, CPU_SMF = Cell phone social media feeling, CPU_SMR = Cell phone social media response.

Test of Normality

The Kolmogorov-Smirnov and Shapiro-Wilk tests of normality for both GPA and PWB were statistically significant ($p < 0.001$), which means that the data for both GPA and PWB was not normally distributed.

Table H.3

Kolmogorov-Smirnov and Shapiro-Wilk Tests of Normality for Grade Point Average (GPA) and Psychological Well-Being (PWB)

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
GPA	0.072	525	0.000	0.964	525	0.000
PWB	0.066	525	0.000	0.976	525	0.000

[a.] Lilliefors Significance Correction.

*$p < 0.001$.

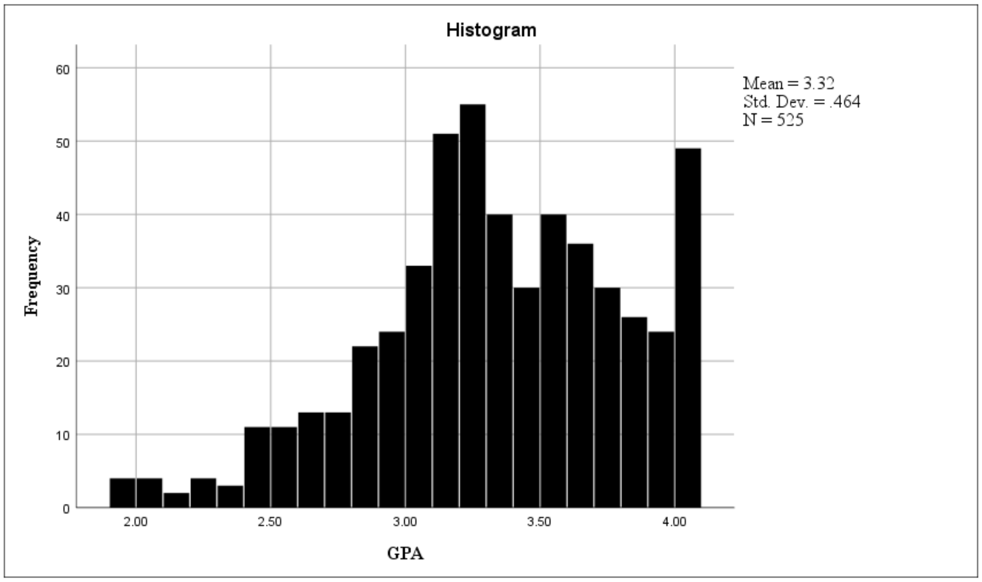

Figure 4. Normality Histogram for GPA.

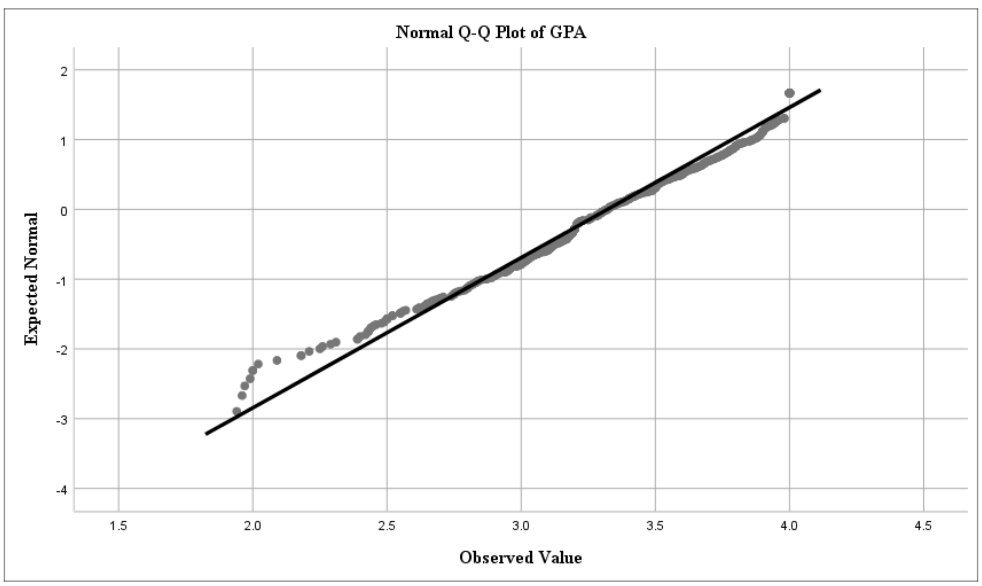

Figure 5. Normal Q-Q Plot for GPA.

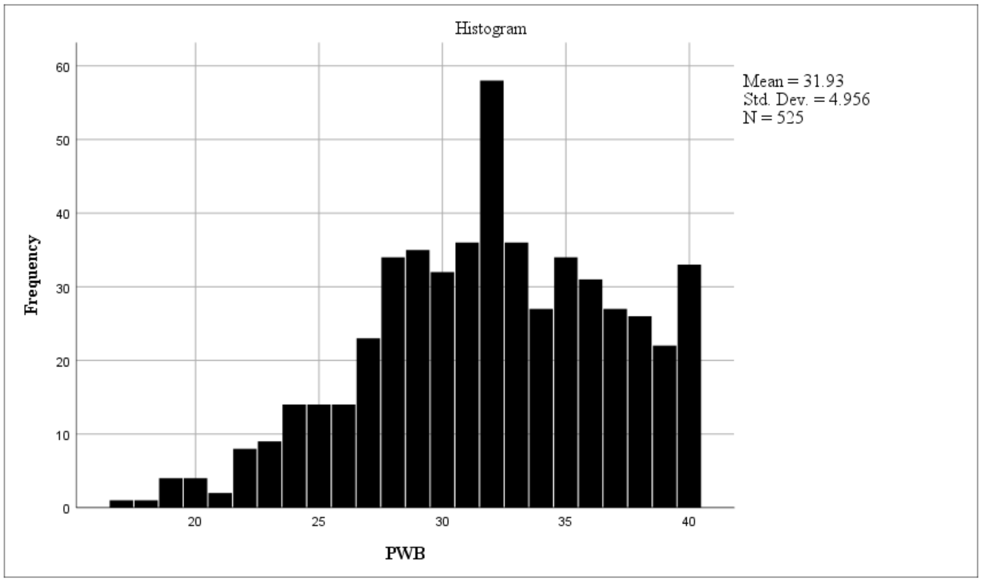

Figure 6. Normality Histogram for Psychological Well-Being.

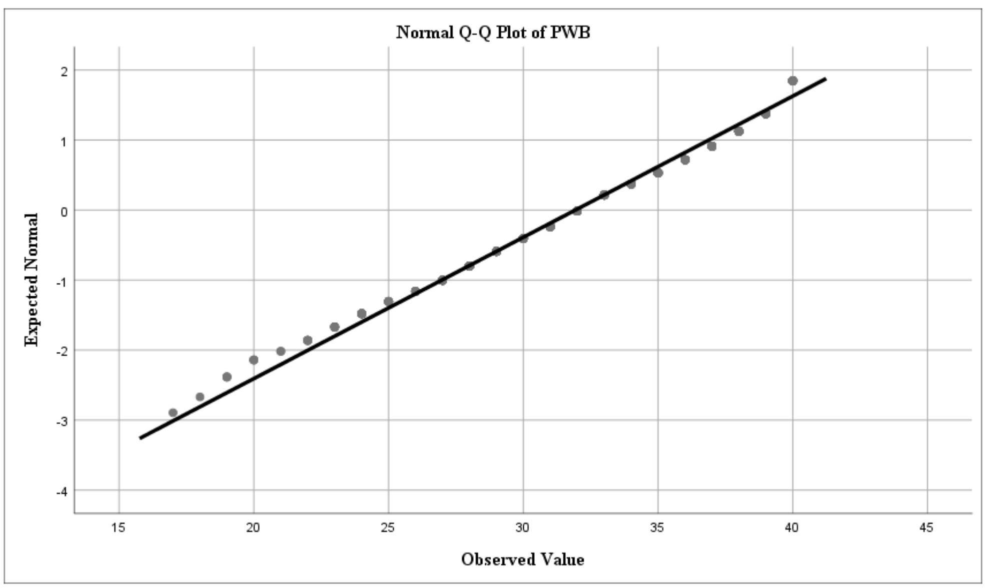

Figure 7. Normal Q-Q Plot for Psychological Well-Being.

APPENDIX I

TEST-STATISTICS

CPU_Total

Table I.1

The Descriptive Statistics of CPU_Total on Sex, Ethnicity, Year in College, and College

Variable	Group	Number (%)	CPU_Total (Mean ± SD)	*p* value
Sex				
	Female	396 (75.4)	10.0 ± 8.37	0.213
	Male	127 (24.2)	8.76 ± 6.68	
Ethnicity				
	Caucasian	241 (45.9)	9.06 ± 7.59	0.009*
	Latinx	133 (25.3)	11.69 ± 9.68	
	Asian	107 (20.4)	8.75 ± 6.93	
	African American	17 (3.2)	12.10 ± 6.63	
Year in College				
	Incoming Freshman	200 (38.1)	10.47 ± 10.63	0.132
	Sophomore	101 (19.2)	10.06 ± 6.56	
	Junior	87 (16.6)	9.33 ± 5.58	
	Senior	71 (13.6)	9.30 ± 5.35	
	Returning Senior	66 (12.6)	7.57 ± 4.95	

College				
	College of Engineering	151 (28.8)	8.58 ± 8.80	0.111
	College of Agriculture and Life Sciences	90 (17.1)	12.01 ± 11.38	
	College of Liberal Arts	82 (15.6)	9.60 ± 5.79	
	College of Science	46 (8.8)	7.52 ± 4.12	
	College of Education and Human Development	45 (8.6)	10.13 ± 6.05	
	Business School	39 (7.4)	9.54 ± 6.75	
	College of Veterinary Medicine and Biomedical Sciences	37 (7.0)	9.50 ± 5.35	

Note. CPU_Total = Total hours-per-day spent using cell phones.

**p* <0.01.

Table I.2

Per Day Cell Phone Use (in Hours) of Undergraduate Students among Ethnicity

	Per Day Cell Phone Use (Hrs.)					
	Ethnicity					
CPU Activity	African American	Latinx	Caucasian	Asian	*p* value	Effect Size
Calling	1.50	0.86	0.75	0.84	0.343	N.S.
Texting	2.46	2.10	1.69	1.57	0.225	N.S.
Taking Photos or Recording Videos	0.41	0.40	0.38	0.32	0.568	N.S.
Listening to Podcasts	0.32	0.44	0.35	0.26	0.659	N.S.
Watching Videos (Netflix, Hulu, etc.)	2.47	2.42	1.56	1.26	<0.001**	Medium
Gaming	0.18	0.43	0.38	0.33	0.892	N.S.
Non-Social Media Internet Browsing (Shopping, surfing, etc.)	0.92	0.88	0.76	0.78	0.953	N.S.

Social Media (Instagram, Twitter, Snapchat, Facebook, etc.)	2.46	3.03	1.97	2.17	0.001*	Small
Email (sending and receiving)	1.03	0.77	0.83	0.80	0.940	N.S.
Other app or software driven use not listed above	0.35	0.42	0.40	0.45	0.980	N.S.
Total Cell Phone Use Per-day	12.10	11.70	9.06	8.76		

Note. CPU = Cell Phone Use, N.S. = Not statistically significant.

*p <0.01, **p <0.001.

CPU_BeforeBed and CPU_Arousal

Table I.3

The Descriptive Statistics of CPU_BeforeBed Bed and CPU_Arousal on Sex, Ethnicity, Year in College, and College

		CPU_BeforeBed		CPU_Arousal	
Variable	Group	Mean ± SD	*p* value	Mean ± SD	*p* value
Sex					
	Female	17.97 ± 4.32	0.011*	14.99 ± 7.46	<0.001**
	Male	16.89 ± 4.21		19.31 ± 10.16	
Ethnicity					
	Caucasian	17.32 ± 3.98	0.136	15.22 ± 7.69	0.171
	Latinx	17.75 ± 4.22		17.02 ± 8.80	
	Asian	18.58 ± 4.94		16.96 ± 9.60	
	African American	17.94 ± 4.84		17.76 ± 8.68	
Year in College					
	Incoming Freshman	17.57 ± 4.14	0.940	15.77 ± 8.21	0.344
	Sophomore	17.86 ± 4.51		17.26 ± 8.74	
	Junior	17.93 ± 4.14		16.24 ± 8.32	
	Senior	17.70 ± 4.34		16.14 ± 9.06	
	Returning Senior	17.45 ± 4.84		14.55 ± 7.57	
College					
	College of Engineering	16.73 ± 4.07	0.010*	16.89 ± 9.17	0.810
	College of Agriculture and Life Sciences	18.28 ± 3.99		16.12 ± 8.19	
	College of Liberal Arts	18.24 ± 3.54		15.80 ± 8.44	
	College of Science	16.63 ± 4.12		16.63 ± 4.12	
	College of Education and Human Development	18.51 ± 4.36		16.20 ± 10.34	
	Business School	18.77 ± 4.80		16.49 ± 8.09	

College of Veterinary Medicine and Biomedical Sciences	17.84 ± 4.67	14.30 ± 6.34

Note. CPU_BeforeBed = The use of cell phone before sleep, CPU_Arousal = The use of cell phones for accessing sexually explicit, violently, or emotionally charged media content.

*p <0.05, **p <0.001

Table I.4

The Cell Phone Use Before Bed of Undergraduate Students among Variable Sex

	CPU_BeforeBed			
	Sex			
CPU Activity	Female (Mean ± SD)	Male (Mean ± SD)	*p* value	Effect Size
Awakened by Calls	1.68 ± 0.76	1.61 ± 0.78	0.619	N.S.
Awakened by Texts	1.64 ± 0.76	1.57 ± 0.70	0.300	N.S.
Awakened by Notifications	1.68 ± 0.77	1.56 ± 0.69	0.137	N.S.
Stayed up late due to Calls	1.84 ± 0.87	1.68 ± 0.78	0.073	N.S.
Stayed up Late due to Texts	2.39 ± 0.86	2.26 ± 0.87	0.120	N.S.
Stayed up Late due to Emails	1.59 ± 0.78	1.49 ± 0.75	0.407	N.S.
Stayed up Late for Listening to Podcast (or Music)	1.60 ± 0.83	1.71 ± 0.81	0.450	N.S.
Stayed up Late due to Social Media	2.79 ± 0.89	2.50 ± 0.91	0.001**	Small
Stayed up Late for Watching Videos	2.76 ± 0.89	2.52 ± 0.87	0.019*	Small

Note. CPU = Cell Phone Use, CPU_BeforeBed = The use of cell phone before sleep, N.S. = Not statistically significant.

* $p < 0.05$, **$p < 0.01$.

Table I.5

The Cell Phone Use Arousal of Undergraduate Students among Variable Sex

		CPU_Arousal			
		Sex			
CPU Activity		Female (Mean ± SD)	Male (Mean ± SD)	*p* value	Effect Size
To Engage In					
	A	4.57 ± 2.81	4.19 ± 2.76	0.392	N. S.
	B	1.85 ± 1.72	3.71 ± 2.68	<0.001*	Large
	C	1.94 ± 1.80	3.39 ± 2.65	<0.001*	Medium
Kept Awake For					
	D	3.62 ± 2.73	3.24 ± 2.43	0.158	N. S.
	E	1.54 ± 1.32	2.50 ± 2.23	<0.001*	Medium
	F	1.46 ± 1.29	2.28 ± 2.04	<0.001*	Medium

Note. CPU = Cell Phone Use, CPU_Arousal = The use of cell phones for accessing sexually explicit, violently, or emotionally charged media content, A = Emotionally charged text messages and images, B = Explicit content pertaining to sexuality (pornography, tinder, dating sites, etc.), C = Explicit content pertaining to violence (video games, movies, etc.), D = Reading or responding to emotionally charged text messages and images, E = Sexually-oriented apps, multimedia, or related materials, F = Violence-based apps, games, multimedia, or related materials, N.S. = Not statistically significant.

*p <0.001

CPU_Switch and CPU_SRLBehavior

Table I.6

The Descriptive Statistics of CPU_Switch and CPU_SRLBehavior on Sex, Ethnicity, Year in College, and College

		CPU_Switch		CPU_SRL	
Variable	Group	Mean ± SD	*p* value	Mean ± SD	*p* value
Sex					
	Female	3.56 ± 4.21	0.111	2.88 ± 0.53	0.011*
	Male	3.40 ± 4.09		2.73 ± 0.62	
Ethnicity					
	Caucasian	3.04 ± 3.61	0.092	2.81 ± 0.55	<0.001**
	Latinx	3.87 ± 4.09		2.80 ± 0.55	
	Asian	4.43 ± 5.65		3.04 ± 0.55	
	African American	2.97 ± 3.13		2.93 ± 0.58	
Year in College					
	Incoming Freshman	3.19 ± 3.24	0.306	2.83 ± 0.57	0.271
	Sophomore	3.43 ± 3.53		2.80 ± 0.57	
	Junior	3.93 ± 4.23		2.88 ± 0.52	
	Senior	3.29 ± 4.47		2.80 ± 0.61	
	Returning Senior	4.35 ± 6.55		2.97 ± 0.49	
College					
	College of Engineering	3.83 ± 5.17	0.080	2.74 ± 0.55	0.151
	College of Agriculture and Life Sciences	2.98 ± 2.91		2.93 ± 0.47	
	College of Liberal Arts	3.93 ± 3.97		2.84 ± 0.58	
	College of Science	2.57 ± 2.34		2.81 ± 0.53	

College of Education and Human Development	3.33 ± 5.12	2.78 ± 0.58
Business School	3.67 ± 4.12	2.89 ± 0.59
College of Veterinary Medicine and Biomedical Sciences	3.43 ± 3.17	2.89 ± 0.66

Note. CPU_Switch = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRL = The use of cell phones for self-regulated learning strategies.

**p* <0.05, ***p* <0.001.

Table I.7

The Cell Phone Use of Undergraduate Students for Self-Regulated Learning Behavior among Variable Sex

	CPU_SRL			
	Sex			
CPU Activity	Female (Mean ± SD)	Male (Mean ± SD)	*p* value	Effect Size
Alarm	3.79 ± 0.56	3.59 ± 0.85	0.002**	Small
Calendar	3.03 ± 1.04	2.95 ± 1.09	0.633	N.S.
Notes	2.31 ± 1.07	2.31 ± 1.09	0.922	N.S.
Clock	2.37 ± 1.11	2.07 ± 1.11	0.019*	Small
Search Engine	3.50 ± 0.69	3.41 ± 0.82	0.306	N.S.
Google Docs	2.62 ± 1.08	2.42 ± 1.12	0.135	N.S.
Email/SM	2.60 ± 1.00	2.36 ± 0.97	0.046*	Small
Text	2.93 ± 0.94	2.84 ± 0.99	0.270	N.S.
Calculator	2.78 ± 0.99	2.62 ± 1.00	0.277	N.S.

Note. CPU = Cell Phone Use, SM = Social Media, CPU_SRL = The use of cell phones for self-regulated learning strategies, N.S. = Not statistically significant.

**p* <0.05, ***p* <0.01.

Table I.8

The Cell Phone Use of Undergraduate Students for Self-Regulated Learning Behavior among Ethnicity

	CPU_SRL					
	Ethnicity					
CPU Activity	African American (Mean ± SD)	Latinx (Mean ± SD)	Caucasian (Mean ± SD)	Asian (Mean ± SD)	*p* value	Effect Size
Alarm	3.71 ± 0.69	3.68 ± 0.72	3.76 ± 0.63	3.79 ± 0.58	0.768	N.S.
Calendar	3.18 ± 1.07	2.95 ± 1.10	2.88 ± 1.06	3.36 ± 0.89	0.008**	Small
Notes	2.53 ± 1.18	2.10 ± 1.07	2.32 ± 1.06	2.61 ± 1.05	0.004**	Small
Clock	2.47 ± 1.23	2.26 ± 1.15	2.25 ± 1.11	2.45 ± 1.08	0.083	N.S.
Search Engine	3.59 ± 0.71	3.50 ± 0.67	3.46 ± 0.74	3.51 ± 0.74	0.837	N.S.
Google Docs	2.59 ± 1.23	2.58 ± 1.07	2.53 ± 1.09	2.81 ± 1.07	0.014*	Small
Email/SM	2.35 ± 0.93	2.51 ± 1.05	2.46 ± 0.94	2.87 ± 0.97	0.011*	Small
Text	2.94 ± 1.03	2.86 ± 0.95	2.87 ± 0.97	3.15 ± 0.89	0.035*	Small
Calculator	3.00 ± 0.79	2.73 ± 1.02	2.74 ± 0.99	2.80 ± 0.99	0.254	N.S.

Note. CPU = Cell Phone Use, SM = Social Media, CPU_SRL = The use of cell phones for self-regulated learning strategies, N.S. = Not statistically significant.

**p* <0.05, ***p* <0.01.

CPU_SMFeeling and CPU_SMResponse

Table I.9

The Descriptive Statistics of CPU_SMF and CPU_SMR on Sex, Ethnicity, Year in College, and College

		CPU_SMF		CPU_SMR	
Variable	Group	Mean ± SD	*p* value	Mean ± SD	*p* value
Sex					
	Female	2.09 ± 0.64	0.431	2.46 ± 0.80	0.051
	Male	2.09 ± 0.66		2.30 ± 0.79	
Ethnicity					
	Caucasian	1.99 ± 0.59	<0.001*	2.40 ± 0.82	0.251
	Latinx	2.13 ± 0.60		2.41 ± 0.76	
	Asian	2.36 ± 0.76		2.54 ± 0.76	
	African American	2.04 ± 0.58		2.40 ± 0.67	
Year in College					
	Incoming Freshman	2.08 ± 0.59	0.333	2.43 ± 0.80	0.343
	Sophomore	2.12 ± 0.67		2.40 ± 0.85	
	Junior	2.04 ± 0.64		2.50 ± 0.82	
	Senior	2.23 ± 0.64		2.46 ± 0.73	
	Returning Senior	2.02 ± 0.77		2.24 ± 0.80	
College					

College of Engineering	2.04 ± 0.70	0.265	2.32 ± 0.84	0.195
College of Agriculture and Life Sciences	2.15 ± 0.67		2.48 ± 0.83	
College of Liberal Arts	2.17 ± 0.60		2.52 ± 0.79	
College of Science	2.04 ± 0.52		2.41 ± 0.67	
College of Education and Human Development	2.07 ± 0.66		2.51 ± 0.71	
Business School	2.10 ± 0.55		2.35 ± 0.74	
College of Veterinary Medicine and Biomedical Sciences	2.16 ± 0.69		2.53 ± 0.86	

Note. CPU_SMF = The use of cell phones for social media feeling, CPU_SMR = The use of cell phones for social media response.

**p* <0.001.

Table I.10

The Cell Phone Use Social Media Feeling of Undergraduate Students among Ethnicity

CPU_SMFeeling						
	Ethnicity					
CPU_SMFeeling	African American (Mean ± SD)	Latinx (Mean ± SD)	Caucasian (Mean ± SD)	Asian (Mean ± SD)	*p* value	Effect Size
Engagement and Connectedness	2.41 ± 0.87	2.59 ± 0.82	2.34 ± 0.83	2.76 ± 0.87	0.001*	Small
Interesting	3.06 ± 0.66	2.89 ± 0.83	2.55 ± 0.80	2.83 ± 0.95	0.001*	Small
Enjoyment	2.59 ± 0.71	2.68 ± 0.93	2.38 ± 0.83	2.77 ± 0.95	0.001*	Small
Meaningful	1.82 ± 0.73	1.86 ± 0.81	1.71 ± 0.77	2.10 ± 0.93	0.022*	Small
Purposeful	1.65 ± 0.70	1.61 ± 0.76	1.50 ± 0.74	2.06 ± 1.00	<0.001**	Medium
Optimistic	1.59 ± 0.71	1.74 ± 0.80	1.66 ± 0.74	1.90 ± 0.91	0.072	N.S.
Belongingness and Acceptance	1.71 ± 0.85	1.89 ± 0.83	1.90 ± 0.81	2.32 ± 0.96	<0.001**	Small

Competent and Accomplished	1.47 ± 0.72	1.77 ± 0.79	1.80 ± 0.81	2.09 ± 0.94	0.010*	Small

Note. CPU_SMFeeling = The use of cell phones for social media feeling, N.S. = Not statistically significant.

**p* <0.05, ***p* <0.001.