



Cell phone use distracts young adults from academic work with limited benefit to self-regulatory behavior

Suresh C. Joshi^{1,2} · Jay Woodward² · Steven Woltering²

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Abstract

We aim to uncover theoretical mechanisms associated with potential negative (i.e., multitasking) and positive (i.e., self-regulation) aspects of cell phone use (CPU) for academic performance in young adults. We hypothesized that, according to the Switch-Load Theory, repeated CPU during academic activities (CPU_Multitasking) would relate negatively, whereas, according to Zimmerman's Theory of Self-Regulated Learning, CPU for self-regulated learning behaviors (CPU_SRLBehavior) would relate positively to the academic performance of undergraduate students. 525 (75.4% female) undergraduate students from a large public university participated in this study during fall 2019 by completing validated quantitative surveys accessing their CPU and academic performance. Spearman's rho was used to compute the correlations and hierarchical regression was used to analyze the variance. Spearman rank-order coefficient showed that CPU_Multitasking relates negatively, but CPU_SRLBehavior is unrelated to the college GPA of undergraduate students. Hierarchical regression showed that CPU_Multitasking was not a significant predictor of academic performance. Young adults who switch to their cell phones during class or study-related activities are more likely to have lower performance in exams as CPU_Multitasking costs time and efficiency (Switch Load Theory). Young adults who use their cell phones for self-regulated learning behavior are less likely to have an impact on their academic performance as CPU_SRLBehavior helps regulate habits but not learning processes. With the known theoretical mechanisms for CPU multitasking and SRL Behavior, this study provides a guiding document for educational computing system practitioners to explore more theory-driven empirical approaches in the field of CPU and academic success.

Keywords Cell phone multitasking · Self-regulated learning behavior · Academic performance · Young adults

Introduction

Cell phones have emerged as all-in-one compact electronic devices in the last two decades that allowed young adults (YA's), aged 18–29 (PEW Research Center, 2011), to work on multiple applications simultaneously at almost any place and point in time (Alessandrini, 2015). These developments may have contributed to American YA's using these devices

exhaustively, resulting in several emotional, cognitive, and psychological issues (Asamoah, 2020; Mark et al., 2014).

The issues included, but were not limited to, loneliness, anxiety, and depression (Boumosleh & Jaalouk, 2017; Kumcagiz & Gunduz, 2016; Sönmez et al., 2020), sleep deprivation (Demirci, Akgönül, & Akpınar, 2015; Joshi, 2022; Joshi et al., 2021; Sohn et al., 2021), psychological disorders (Pera, 2020; Yuan et al., 2021), attention deficit and hyperactivity disorder (Kwon et al., 2020), substance addictions (Massey et al., 2021), social relationships (Annoni et al., 2021; Chen & Peng, 2008); and lower academic achievements (Sapci et al., 2021; Uzun et al., 2019). Lower academic achievement was related to young adult cell phone use (CPU) both inside and outside the classrooms (Le Roux & Parry, 2021; Rosen et al., 2013). The use of cell phones during a class/lecture, lab, and/or study session may be detrimental to academic performance, therefore, needs to be investigated.

✉ Steven Woltering
swolte@tamu.edu

¹ Centre for Continuing Education, University of Petroleum and Energy Studies, Knowledge Acres, Kandoli, Dehradun, India 248007

² Department of Educational Psychology, Texas A&M University, 718B Harrington Tower, College Station, TX 77843-4225, USA

Young adults, a high representation of college students (Amez & Baert, 2020), are the largest demographic users of cell phones ("Demographics of mobile device ownership and adoption in the United States," 2021), as a result, the young adult cell phone ownership has reached saturation (Hitlin, 2020). YA's use cell phones for various purposes but mainly for checking social media notifications, playing games, gathering information, and connecting with others (Wheelwright, 2021). The classroom CPU of college students includes texting during the class 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). College students spend 8 to 10 h daily, with female students spending more time (10 h.) than male students (8 h.), on their cell phones (Roberts et al., 2014). These numbers increased up to 20–30% on average during the COVID-19 pandemic (Meyer et al., 2020). Despite higher CPU hours, the negative effect of cell phone addiction on school performance was found to be less severe in the case of female students as compared to male students (Nayak, 2018). Of note was the fact that college students are engaged with their cell phones day and night (Perrin & Atske, 2021; Thomée et al., 2010). With such constant CPU, college students are left with reduced time for academic activities ("Time spent on average on a smartphone in the U.S., 2021," 2021). College life is a crucial phase where academic achievements impact the life-altering decisions of college students (Green & Celkan, 2014; Rugutt & Chemosit, 2005), and CPU pertains of paramount importance as it may affect their academic performance.

There were several activities/operations/applications of cell phones that were associated with positive aspects of CPU. For example, accessibility and mobility were the foremost key components associated with the positive aspect of the use of cell phones as the availability and the ease of use make cell phones "anytime-anywhere" kind of handheld devices with high mobility (Zhang et al., 2014; Lepp et al., 2014). Information gathering and communication were other key components associated with the positive aspect of CPU due to the convenience of gathering information and communicating that information to others "anytime-anywhere" (Chen & Ji, 2015; Lepp et al., 2015). The psychological variables such as self-efficacy and behavioral intentions were found to be associated with the positive aspect of CPU for learning. For example, behavioral intentions of using cell phones for learning helped young adults improve their self-efficacy, which further helped them improve their academic achievements (Han & Yi, 2018).

CPU was found to be associated with both negative and positive aspects, however, was not examined using quantifiable variables in terms of both the aspects separately. The present study investigates the potential negative and positive

effects of CPU on academic functioning using up-to-date quantifiable measures.

The following research questions will serve as the inquiry guidelines for this study:

RQ1: How does the frequency of cell phone checking during a class/lecture, lab, and/or study session (CPU_Multitasking) of undergraduate students correlate to their academic performance?

RQ2: How does the use of cell phones for self-regulated learning behaviors (CPU_SRLBehavior) of undergraduate students correlate to their academic performance?

Literature review

Scope and coverage of CPU and academic performance in college students

Over two-thirds of college students use cell phones to complete their academic tasks (Jacobsen & Forste, 2011), in fact, 83% use them "for course-related activities for one or more of their courses" (Seilhamer et al., 2018). Research indicated that college students had a positive outlook on the use of cell phones for academic purposes as these devices provided the flexibility of time and place in achieving academic goals with little or no effort (Tossell et al., 2015). The aforementioned study revealed that even though participants perceived the use of smartphones for university education as favorable prior to use, later they thought it was harmful to their academic achievement. The authors concluded that "participants reported that their iPhones were more of a distraction than a help, and they had noticed large changes in habitual behaviors associated with the need to continuously check their iPhone" (pp. 720–721). Research also indicated that college students feel motivated to use cell phones for learning, and the majority of them (71%) believe that CPU for learning makes them more productive (Fernandez, 2018).

The data on classroom CPU showed that 94% of college students wanted to use their cell phones in class from which one-third of the students believed that classroom CPU "has improved their ability to learn and retain information" (Kelly, 2017). College students also believe that CPU enhanced their learning processes, assisted them with learning, and helped them make their overall learning effective (Fernandez, 2018). A majority of college students (90–97%) said they were aware of their classmates' CPU during a class (Berry & Westfall, 2015), most of them, approximately 77%, were not bothered by it (Pettijohn et al., 2015). In sum, cell phones, with countless operations and Apps, engaged college students in classrooms and occupied a significant amount of their time meant for academic activities. Such high classroom cell phone occupancy may

affect the academic performance of YA's and thus needs to be investigated.

Existing literature

Previous studies, to date, provided arguments for both positive and negative aspects of young adult CPU for academic performance (Amez and Baert, 2020; Kocak, Goksu & Goktas, 2021; Lin et al., 2021). Positive aspects included accessibility and mobility (Zhang et al., 2014; Lepp et al., 2014), simplicity of information gathering, and ease of communication (Chen & Ji, 2015; Lepp et al., 2015), and improved self-efficacy and behavioral intentions of using cell phones as helpful tools for learning (Han & Yi, 2018). YA's, with high self-efficacy and judicious use of cell phones for academic tasks, had greater benefits of CPU for their academic success. Researchers were 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). Authors 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 to the overall GPA of college students. Negative aspects included (attention-drawing) classroom notifications (Junco & Cotten, 2012; Kim et al., 2021), multitasking and task-switching (Alvarez-Risco et al., 2020; Uzun & Kilis, 2019), "fear of missing out" (Chen & Yan, 2016), lack of motivation or a sense of boredom (Hawi & Samaha, 2017), and cell phone addiction (Lisewski et al., 2020; De-Sola Gutiérrez et al., 2016). YA's, encountered with negative aspects of CPU for academic performance, scored poorly in exams (Uzun & Kilis, 2019). CPU leads to better academic performance when used wisely, however, leads to poor academic achievements with misuse or overuse.

For college students, cell phones were equally important as other learning tools such as textbooks. Almost all college students bring their cell phones to class (Tindell & Bohlander, 2012), but most of them put these devices in "vibrate" or "silent" mode (Berry & Westfall, 2015). Authors Pettijohn et al. (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 mentioned other responses such as work, business,

or avoiding disturbing the class by leaving the classroom to check cell phones. In a recent study, 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 min of CPU, and the impact of CPU during class/study time was almost double than that of CPU outside/free time (Felisoni & Godoi, 2018). These studies suggested that carrying a cell phone to the classrooms creates 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.

The use of cell phones inside and outside the classroom at different times and for different purposes affected academic performance differently. For example, CPU during class/study impacted GPA negatively, however, CPU at night was found to be unrelated to academic performance (Li et al., 2015). Further, CPU per day influenced performance measures differently because the daily in-class CPU was negatively associated with the test scores, irrespective of actual in-class CPU time (Bjornsen & Archer, 2015). Studies have indicated that college students often switch from class and/or study to checking cell phone notifications (Rosen et al., 2013). Such frequent switches add up and lead 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 to daily CPU hours. 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). From all CPU usages, 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 the overall GPA of college students (Junco & Cotten, 2012). However, social media usage, such as Facebook'ing and Twitter'ing, impacts GPA more severely than texting (Bjornsen & Archer, 2015), as college students spend more time on social media (Wood, 2018).

Emerging mechanisms

Two potential mechanisms have emerged from the existing literature on young adult CPU and academic performance that have not been tested directly. The first mechanism was classroom multitasking, termed CPU_Multitasking, which we defined as switching back and forth between cell phones and academic tasks during a class/lecture, lab, and/or study session. CPU_Multitasking was associated with negative implications of CPU on academic performance as it was found to be negatively correlated with the academic performance of YA's.

The second mechanism was self-regulated learning behavior, termed CPU self-regulated learning behavior (CPU_SRL-Behavior) in this study, which we defined as the use of cell phones for self-regulated learning behaviors such as using an alarm, calendar, calculator, notes, Google Docs, timer, emails, and texts. CPU_SRLBehavior was associated with positive implications of CPU on academic performance as it helped YA's improve their learning outcomes.

Underlying theory for CPU multitasking

The underlying theory for detrimental effects of CPU multitasking can be based on Switch-Load Theory (Adler & Benbunan-Fich, 2013; Rubinstein et al., 2001). YA's switch back and forth between cell phones and academic tasks, which has been associated with time loss and switch-cost, the loss of efficiency in responses caused due to task-switching (Rubinstein, et al., 2001). Task-switching dilates response time, even when switching takes place between two predictable tasks. Dilation of response time due to task-switching decreases productivity. Switching cost significantly increases in cases of switching between complex tasks. The significant effects of switch cost can be seen in cases of switching between relatively unfamiliar tasks (Rubinstein et al., 2001).

Empirical findings concerning CPU multitasking and academic performance

Young adults use cell phones in the classroom and become involved in multitasking and task switching (Alvarez-Risco et al., 2020; Uzun & Kilis, 2019). CPU in the classroom includes texting, calling, and social media (Felisoni & Godoi, 2018; Lepp et al., 2015). CPU-based classroom multitasking distract YA's (Patterson, 2016; Junco & Cotten, 2012). Such CPU distractions steal study time both inside and outside the classroom resulting in YA's losing track of their educational goals (Rosen et al., 2013). Although all cell phone operations may contribute to multitasking, texting alone was found to have a significant impact on the actual grade point average (GPA) of college students (Berry & Westfall, 2015; Gingerich & Lineweaver, 2014; Lepp et al., 2014). Other cell phone operations such as calling and social media also lead to low college grade point averages of YA's (Junco & Cotten, 2012). Since classroom cell phone multitasking can affect the academic performance of YA's it is important to be investigated.

Underlying theory for CPU self-regulated learning behavior

A theory that can connect positive aspects of self-regulated learning (SRL) behavior and CPU is the Self-Regulated Learning Theory (Zimmerman, 1989). This theory is based

on "how students personally activate, alter, and sustain their learning practices in specific contexts" (Zimmerman, 1986, p. 307). Students need to "control contextually specific cognitive, affective, and motoric learning processes" with "varying amounts of selectivity and structuring in order for them to learn" (p. 307). Metacognitive (self-instruct, self-monitor, and self-evaluate), motivational (self-efficacious and autonomous), and behavioral (select, structure, and create environments) SRL strategies helped students to actively participate in their own learning (Zimmerman & Moylan, 2009) and were found to be related to improved academic performance (Usher & Schunk, 2018; Zimmerman & Martinez-Pons, 1986). Cell phone operations of different kinds may help YA's in regulating metacognitive, motivational, and behavioral learning behaviors for academic activities, which may further improve their academic performance.

Empirical findings concerning CPU self-regulation and academic performance

Empirical research examining the relationship between SRL and CPU has generally supported a positive relationship (Han & Yi, 2018; Troll et al., 2021), however, few studies have shown no relationship between the two variables (Hartley et al., 2020). A study by Han and Yi (2018) found that increased familiarity with cell-phone-mediated communication (CPMC) helped college students improve their self-efficacy and behavioral intentions, and less usage of cell phones as learning tools adversely influenced their academic performance. Another study by Fernandez (2018) found that improved self-efficacy and self-regulated behaviors helped college students enhance their CPU perceptions of learning, which in turn improved their academic performance. However, CPU-based SRL, focusing on the resource management component of SRL, had no direct impact on the academic achievement of YA's (Hartley et al., 2020). In a recent study, college students with higher self-control showed better academic performance, although effective handling of cell phones such as CPU procrastination, placement habits (placing the cell phone in a bag), and setting habits (putting cell phone on silent mode) were attributed to this improvement (Troll et al., 2021). High CPU, CPMC, and self-regulated learning behaviors may influence academic performance differently, therefore, needs to be investigated using measures quantifiable in terms of the latest CPU operations. CPU for SRL behaviors could be 1) task reminders such as alarm, calendar, timer, stopwatch, or clock function, 2) note writing cell phone operations such as notes and Google Docs, 3) communication-based cell phone operations such as texting and emailing, and 4) mathematical function based operation such as a calculator.

The present research: anticipated outcomes and the significance to the field

Study rationale, problem statement, and research hypotheses

Investigating CPU in college students is imperative because the precise relationship between CPU and academic performance is unclear due to the possibility that some uses can have detrimental effects whereas others may provide positive effects. Moreover, the theoretical mechanisms behind the negative and positive effects of CPU on academic performance were unknown. The present study, therefore, aims to examine the CPU and academic performance of YA's using an updated instrument measuring both the mechanism, i.e., CPU_Multitasking and CPU_SRLBehavior at work (during a class/lecture, lab, and/or study session and for the tasks on a daily basis).

Following research hypotheses were developed to answer the research questions of this study:

H1: We expect, according to the switch-load theory, the frequency of cell phone checking during a class/lecture, lab, and/or study session (CPU_Multitasking) to negatively relate to the academic performance (GPA) of undergraduate students;

H2: We expect, according to Zimmerman's theory of self-regulated learning, the use of cell phones for self-regulated learning behaviors (CPU_SRLBehavior) to relate positively to academic performance (i.e., college GPA) of undergraduate students.

Significance to the field

We believe that the outcomes of this study will be valuable to both academics and policymakers, especially from the areas of human–computer interaction, educational computer systems, cell phone addiction, attention-retention, and self-regulation in various ways. For example, firstly, as we measure the frequency of checking cell phones during an academic task and the use of cell phones for self-regulated learning behaviors for the latest cell phone operations/activities, we explicitly provide scholars with the updated quantifiable measures of CPU_Multitasking and CPU_SRLBehavior. Secondly, as we investigate underlying theories for CPU_Multitasking and CPU_SRLBehavior, we uncover theoretical mechanisms associated with the potential negative and potential positive aspects of CPU for academic performance. Thirdly, while previous studies provide a viewpoint about the association between CPU and academic performance, we provide a

more precise picture of the relationship by examining the potential mechanisms at work (during a class/lecture, lab, and/or study session and for the tasks on a daily basis). Lastly, as we connect the quantitative data with the underlying theories for CPU_Multitasking and CPU_SRLBehavior, we provide empirical validity to the theoretical mechanisms for the potential negative and positive correlations of CPU on academic performance.

Methods

Participants

The sample consisted of undergraduate students ($N = 525$) between 18 and 29 years old, with an average age of 20 years ($SD = 3.18$). In this sample, 83% of undergraduate students were between 18 and 21 years old and 17% were between 22 and 29 years old. From this sample, 75% of the participants were female, 24% male, and 1% of the participants preferred not to answer. It was an ethnically diverse sample of participants comprising 49% Caucasian, 24% Latinx, 19% Asian, 3% African American, 1% Native American, while 3% identified as “other” in the survey. The remaining 1% preferred not to answer. The data was collected during fall 2019 when the undergraduate student population comprised 59% Caucasian, 25% Latinx, 9% Asian, 3% African American, and 3% “others” (“Student data and reports,” n.d.).

The respondents were selected from a large southwestern University in the USA from fourteen different colleges and majors, including the College of Engineering (29%), the College of Agriculture and Life Sciences (17%), the College of Liberal Arts (16%), the College of Science (9%), the College of Education and Human Development (9%), Mays Business School (7%), and the College of Veterinary Medicine and Biomedical Sciences (7%). The sample was also diverse in terms of the number of years the participants have been attending a two-year or four-year higher institution, as it included 38% incoming freshman, 19% sophomore, 17% junior, 14% senior, and 13% returning senior. Our sample was largely reflective of the university population with a margin of error of $\pm 4.25\%$ at a 95% confidence level.

Procedures

An online quantitative survey was designed using psychometric principles aligned with best practices for constructing an online assessment tool (Bethlehem & Biffignandi, 2011; Couper, 2008). All enrolled undergraduate students were invited for voluntary participation by email invitations distributed through the university's listserv. The link on the invitation email would take the invitees to an online survey software (Qualtrics) webpage. This webpage would have

informed consent, required from undergraduate students, on the first page. Prospective participants were able to read all the necessary information regarding their participation in the study before electronically signing the informed consent. Those who submitted their informed consent by clicking the “I Agree” button got access to the survey. The survey was compatible with mobile devices as it was presumed students with high cell phone use would prefer this interface method.

Measures

Academic performance measures

Self-reported GPA was used to assess undergraduate students' academic performance as these were valid measures of academic performance (Kuncel et al., 2005). Suitable measures were taken to reduce the probability of getting intentionally inflated scores. It was made clear to the participants that their GPA will be purely self-reported and that they will have no gain from misrepresenting it. Further, no identifiers were collected from the participants to reduce the effect of intentionally inflated scores. In addition, participants had no direct benefits except raising awareness for using cell phones during a class/lecture, lab, and/or study session. High school GPA was 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).

CPU questionnaire

We developed a comprehensive survey comprising of 19 items to measure CPU_Multitasking and CPU_SRLBehavior. Ten items from the construct CPU_Multitasking measured the frequency of cell phone checking during a class/lecture, lab, and/or study session. Nine items from the construct CPU_SRLBehavior measured the use of cell phones for self-regulated learning behaviors. We have ensured that our questions were up-to-date, suited to our research questions, sensitive to the academic context, and consistent in format and presentation, which was solely based on the validated scales used in the previous studies. In doing so, we adhered to using psychometric principles aligned with best practices for constructing an online assessment tool (Bethlehem & Biffignandi, 2011). The vast majority of our items were adapted from existing scales. Some items were extended, and the language was modified to make them clearer and more understandable by making moderate modifications. The scales with the moderate modifications require “a more thorough assessment of the psychometric adequacy of the measure or the extent to which its properties are similar to the original measure” (Stewart et al., 2012, p. 7). A detailed assessment of the psychometric adequacy of the measures

was conducted, and it was found that these modifications did not alter the empirical validity of the scales for data analysis or interpretation purposes. Before administering the main study, the internal consistency of the items was tested in two separate pilot studies (refer to Appendix A for more details). For each of the CPU subscales, we provide a detailed account of the modifications and sources that were used in the supplements (please refer to Appendix B for more details).

Translational validity was assessed using face and content validity (Drost, 2011; Durlak, 2009). To test the face validity, the survey was administered to two professional development specialists from the Center for the Advancement of Literacy & Learning at the university. The feedback from both the specialists were implemented in the instrument. To test content validity, 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 and positively evaluated the instrument on a number of criteria, such as “Whether or not the items in the instrument effectively capture what was intended to measure.”, “Linguistic consistency and content validity of extended/modified items.”, and “Overall alignment of the items within constructs, as well as within the overall instrument, when brought together in one scale.”

The internal consistency of the items was measured using the sample from the current study ($N = 525$; 75% female). The first subscale, i.e., CPU_Multitasking, consisted of ten items, with a minimum possible score of 1 and a maximum possible score of 40. All the items in the CPU_Multitasking construct were found to exhibit an excellent internal consistency (Cronbach's $\alpha = 0.93$). The second subscale, i.e., CPU_SRLBehavior, consisted of nine items, with a minimum possible score of 1 and a maximum possible score of 4. All the items in the CPU_SRLBehavior construct were also found to exhibit good internal consistency (Cronbach's $\alpha = 0.75$). The overall scale consisted of strong reliability (Cronbach's $\alpha = 0.89$) for the designated sample.

Data analysis

The statistical package SPSS for Windows (Version 25.0, Chicago, IL, USA) was used for all analyses. Multicollinearity for independent variables was tested using the Variance Inflation Factors (VIF) method. The VIF value of 1 indicate that the predicting variables stand isolate, and the VIF value between 1 and 5 indicate a moderate correlation but not enough to influence the regression, which does not warrant corrective measures (Fox & Monette, 1992). CPU_Multitasking ($VIF = 1.30$) and CPU_SRLBehavior ($VIF = 1.19$) were found independent for the regression purposes as determined by the VIF analyses.

Nonparametric correlations (Spearman's rho) were used to compute the correlation between CPU variables (CPU_Multitasking and CPU_SRLBehavior) and GPA. Hierarchical regression was used to estimate whether CPU variables explained a statistically significant amount of variance in GPA after accounting for all other variables. To maintain rigor and quality in the outcomes, a control analysis was also administered for the dependent variables before conducting the main analyses. The control analysis consisted of the test of skewness, homoscedasticity, and normality for the variable GPA. One-way ANOVA and post-hoc analyses were used to calculate the difference between the groups, and the significance level was set as 0.01 for the analyses. The partial eta squared was used to determine the effect size between the groups (significance level = 0.01) because this method takes all level categories into account (Durlak, 2009; Lakens, 2013). For a univariate ANOVA, the effect size for the outcome variable with a partial eta squared value of 0.01 is considered small, 0.06 is considered medium, and 0.14 is considered large (Lakens, 2013).

Results

Descriptive statistics

Undergraduate students switched between academic task and cell phones three to four times during a class/lecture, lab, and/or study session, with an average of 3.52 (SD = 4.18), on a scale of 0 to 40, during a 60-min class/lecture, lab, and/or study session for various reasons (Table 1). There were no statistically significant ($p < 0.01$) differences between the group means of variables sex, ethnicity, year in college, and college for CPU_Multitasking, as determined by a one-way ANOVA (Table 4, Appendix C).

Undergraduate students “often” (score; 2.73 – 3.04) used cell phones for SRL behaviors on a scale ranging from 1 to 4, with 1 being “Never” and 4 being “Always.” The variable sex ($F(2, 522) = 4.588, p < 0.01, \eta^2 = 0.02$) and ethnicity ($F(6, 518) = 4.102, p < 0.001, \eta^2 = 0.05$)

Table 1 The descriptive statistics of continuous variables age, CPU_Multitasking, CPU_SRLBehavior, and GPA (N = 525)

	Minimum	Maximum	Mean \pm SD	Mode
Age	18	29	20.19 \pm 3.18	18.00
CPU_Multitasking	0.00	40.0	3.52 \pm 4.18	1.10
CPU_SRLBehavior	1.33	4.00	2.84 \pm 0.56	3.00
GPA	1.63	4.00	3.32 \pm 0.47	4.00

CPU_Multitasking = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRLBehavior = The use of cell phones for self-regulated learning behavior, GPA = Grade Point Average

had a statistically significant ($p < 0.01$) effect on the CPU_SRLBehavior of undergraduate students, as determined by a one-way ANOVA (refer to Table 5, Appendix C for more details). The CPU_SRLBehavior of female undergraduate students (2.88 ± 0.53) was higher than that of male undergraduate students (2.73 ± 0.62). The variable sex had a small impact on undergraduate students' use of cell phones for self-regulated behavior, such as alarm, timer/stopwatch/clock, and email and social media. Female undergraduate students, as compared to male undergraduate students had higher mean scores for all CPU_SRLBehavior listed. 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_SRLBehavior. The variable ethnicity had a small effect on undergraduate students' use of cell phones for self-regulated behavior, such as calendars, 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_SRLBehavior (Table 6, Appendix C).

Inferential analysis

Spearman rank-order correlation was used to assess the correlation of GPA with CPU_Multitasking and CPU_SRLBehavior (Table 2) and a hierarchical regression was administered to see how the CPU variables (CPU_Multitasking and CPU_SRLBehavior) predicted the GPA of undergraduate students (Table 3).

H1 was supported. The frequency of CPU during a class/lecture, lab, and/or study session (CPU_Multitasking) was negatively correlated to the GPA of undergraduate students (Table 2). Hierarchical regression showed that the ANOVA results of the model were statistically significant ($R^2 = 0.02, F(12, 511) = 1.92, p < 0.05$), which means that the model can explain the variability within the data set. CPU_Multitasking was not a significant predictor of the academic performance of undergraduate students as the beta coefficient of CPU_Multitasking ($Beta = -0.05$) was not statistically significant (Table 3). Combining correlation and regression outcomes, CPU_Multitasking correlates negatively with the GPA of undergraduate students, however, cannot be used as a predictor for GPA. Conclusively, undergraduate students switched to their cell phones during a class/lecture, lab, and/or study session, which negatively correlated with their academic performance.

H2 was not supported. The Spearman rank-order coefficient for CPU_SRLBehavior was not statistically significant ($0.002, p = 0.961$) (Table 2). The CPU_SRLBehavior of undergraduate students was unrelated to their GPA. It means the use of cell phones for SRL behaviors, such as using an alarm, calendar,

Table 2 Nonparametric correlations (N = 525)

		CPU_Multitasking	CPU_SRL	GPA
Spearman's rho	CPU_Multitasking	1.000		
	CPU_SRLBehavior	0.309**	1.000	
	GPA	-0.094*	0.002	1.000

CPU_Multitasking = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRLBehavior = The use of cell phones for self-regulated learning behaviors, GPA = Grade point average

* $p < 0.05$ (2-tailed); ** $p < 0.01$ (2-tailed)

Table 3 Hierarchical Regression of Demographics and Cell Phone Use Variables on Grade Point Average

Variables	Grade Point Average (Beta Coefficients)	SE	95% CI
Demographic information			
Sex	-0.01	0.045	(-0.082—0.095)
Age	0.01	0.006	(-0.010—0.015)
Ethnicity	-0.12*	0.015	(-0.011—0.049)
Colleges	-0.01	0.011	(-0.032—0.007)
Years in college	0.04	0.014	(-0.047—0.009)
Cell phone use variables			
CPU_Multitasking	-0.05*	0.005	(-0.017—0.004)
CPU_SRLBehavior	0.02	0.031	(-0.045—0.107)
Adjusted R^2	0.02		
N	524		

All betas are standardized coefficients. CPU_Multitasking = The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRLBehavior = The use of cell phones for self-regulated learning behaviors, SE = Standard error coefficients, CI = Confidence interval

* $p < 0.05$

calculator, notes, Google Docs, timer, emails, and texts did not correlate with undergraduate students' academic performance.

Our study did find that CPU_Multitasking was highly correlated with CPU_SRLBehavior of undergraduate students (0.309, $p < 0.001$), which could help address issues concerning CPU_Multitasking during a class/lecture, lab, and/or study session. The measures concerning CPU_SRLBehavior, whether in terms of GPA or CPU_Multitasking, may have potential benefits for young adult CPU but warrant further research in these areas. Combining the outcomes of correlational analysis and ANOVA together, 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_SRLBehavior did not correlate with their academic performance.

Discussion

Concerning our first hypothesis, CPU_Multitasking was negatively correlated to the GPA of undergraduate students. Students reported checking their cell phones around 4 times during a 60-min class/lecture, lab, and/or study session.

These results were consistent with previous studies demonstrating the negative correlation between CPU_Multitasking and GPA (Jacobsen & Forste, 2011; Rosen et al., 2013) of college students. Switching between two relatively unfamiliar tasks, such as class/lecture and CPU, possibly made these students less efficient (Rubinstein et al., 2001). Further, the switching 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 correlates with GPA negatively.

Although the results of this study were consistent with the previous studies, we argue that the outcomes were not completely in line with those studies. For example, in our study, switching between CPU and class/lecture and/or study session was not a significant predictor of academic performance. Moreover, CPU_Multitasking had no statistically significant effect ($p = 0.117$) on the GPA of undergraduate students. However, previous studies indicated that CPU_Multitasking was a

significant predictor of college student's academic performance (Bjornsen & Archer, 2015; Li et al., 2015). Like Li et al. (2015), who have found in-class CPU to be a negative predictor of GPA, the present 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 that factors such as understanding of class content and interest in class/lectures 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 test grades.

Concerning our second hypothesis, the CPU_SRLBehavior did not correlate with undergraduate students' academic performance. These results aligned with the finding from a previous study on the SRL 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." 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. According to Bandura (1991), self-regulatory mechanisms are centered on self-monitoring, judgment on one's behavior, and affective self-reaction. We argue that cell phone activities/operations may help regulate habits but may not be directly related to learning behaviors concerning judgment on one's behavior and affective self-reaction. More specifically, digital devices such as cell phones can be used for monitoring habits, however, may not be used for assessing learning behaviors and affective self-reactions.

Previous studies have assessed the 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_SRLBehavior, 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_SRLBehavior: calendar, notes, Google docs, email and social media, and texts. The CPU_SRLBehavior, however, did not correlate with the academic performance of undergraduate students. Here again, we argue that learning behaviors and processes should be given priority over habits as former is closely related to academic performance (Bandura,

1991). Quantifiable measures of CPU activities/operations relating to metacognitive, motivational, and behavioral SRL strategies will help better understand the impact of CPU_SRLBehavior on academic performance as those measures would directly assess student engagement in learning activities.

Limitations

While this study has produced several novel and practical findings, there are limitations to be considered when interpreting the results. Though the outcomes of this study are generalizable to the larger population of undergraduate students, the sample, composed of undergraduate students from a single public university in the Southwestern United States, may restrict the outcomes to the socio-economic and cultural specificities of university students from this region. The sample also suffered from overrepresentation, especially for female participants (75%). The sample was a good representation of the undergraduate student population at the university where the study was conducted, however, it may not be an accurate representation of the racial composition of the undergraduate student population in the US as a whole, specifically with the population identified as African American. In addition, the sample may pose the overrepresentation of Asian undergraduate student population at the university as well as in the US.

The measures relied on self-report which lead to another limitation of this study. Recall bias is the key concern about self-reported questionnaires; however, other factors occurring while participants took the survey including living, non-academic workload, studies, leisure activities, family, and social commitments cannot be ruled out. It is argued that "subjective measures can sometimes provide accurate and efficient assessments of objective states," such as physical functioning (Cleary, 1997). However, subjective 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 (Abernethy, 2015). Finally, due to the correlational nature of the study, causality cannot be inferred from the results.

Conclusion

This study was designed to answer the following research questions 1) How does the frequency of cell phone checking during a class/lecture, lab, and/or study session (CPU_Multi-tasking) of undergraduate students correlate to their academic performance? 2) How does the use of cell phones for self-regulated learning behaviors (CPU_SRLBehavior) of undergraduate students correlate to their academic performance? Findings suggest that YA's switch back and forth between cell phones and academic tasks, which resulted in a switch-cost. The loss of learning efficiency due to task-switching could

result in lower grades. Findings also suggest that CPU_SRL-Behavior did not correlate with the academic performance of YA's, which leads to the conclusion that CPU_SRLBehavior may help regulate habits but not learning processes. However, more research is needed in this area.

This study provides some unique learning outcomes compared to the existing research on CPU and academic performance to date. First, the study provides clarity on the correlation between CPU and academic performance by examining a potential mechanism (during a class/lecture, lab, and/or study session and for the tasks on a daily basis), which will help researchers explore a new, quantifiable dimension concerning CPU. Second, the analyses for both the assessed aspects of CPU, CPU_Multitasking, and CPU_SRLBehavior were supported by theoretical mechanisms (i.e., Switch-Load Theory and Self-Regulated Learning Theory), which sharpened our measures and made our findings more precise and meaningful. Third, this study provides useful insights for the design and the use of cell phones as educational computer systems, as the study employed a theory-driven empirical approach. This approach was the first of its kind in the scientific literature concerning the use of cell phones for educational activities and may help guide researchers and policymakers for future research and development. For example, as “mini” educational computer systems, developing cell phones with more Apps that limit CPU and reduce distraction and cognitive load or having students use such Apps or settings during a class/lecture, lab, and/or study session may be one of the best ways to increase academic performance.

Practical significance of the study outcomes: implications for educational settings

The findings from this study provide insights into both negative and positive aspects of young adult CPU for academic performance, which can have important practical significance for researchers and policymakers. The outcomes can also have implications for improving learners' achievements in educational settings.

Concerning the negative aspects, the CPU_Multitasking hypothesis educates us about the harmful effects of switching back and forth between cell phones and academic tasks. It also describes the recurring effect of switching between tasks multiple times. The hypothesis further explains the reason for the recurring effect and the way it impacts student efficiency in focusing on class/lecture and/or study. These findings will help college students make informed decisions about the use of cell phones, especially during academic tasks such as a class/lecture and/or study time. The outcomes will also help classroom practitioners create instructional guidelines about restricting the use of cell phones during a class/lecture and/or study session.

For decades, classroom cell phone multitasking has been a major area of concern for academics, researchers, and policymakers, especially in the domain of higher education (Alvarez-Risco et al., 2020; Uzun & Kilis, 2019; Felisoni & Godoi, 2018; Patterson, 2016; Junco & Cotten, 2012). Knowing the switching frequency for cell phone activities/operations, i.e., texting, calling, emailing, shopping, banking, surfing the internet for social media purposes, and gaming influencing academic performance will educate academics, researchers, and policymakers about the severity of the problem and will help them develop guidelines for educational settings comprising the college student population. Also, having a theoretical mechanism for CPU_Multitasking and academic performance can guide researchers in developing other dimensions of the Switch Load theory such as testing the theory for various levels of task complexity. Such interventions will help researchers better understand the cognitive processes involved in multitasking and task-switching better.

Concerning potential positive aspects, the CPU_SRL-Behavior hypothesis, suggests on the basis of our study, that the use of cell phones for SRL behaviors, such as using an alarm, calendar, calculator, notes, Google Docs, timer, emails, and texts are not directly related to academic performance in typical student populations.

This outcome has two practical implications. First, we learned that cell phone activities/operations may help regulate habits but may not be directly related to learning behavior driven by self-regulative mechanisms (Bandura, 1991). “Self-regulatory mechanisms operate 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). One can argue that CPU SRL activities may help monitor one's self (personal) but do not influence determinants such as judgment of one's behavior and affective self-reaction.

Second, we learned about the need to define and categorize CPU activities/operations in terms of quantifiable metacognitive, motivational, and behavioral SRL strategies that can help students actively engage in their learning [processes]. Metacognitive strategies will help students self-instruct, self-monitor, and self-evaluate, motivational strategies will help regulate self-efficacy and autonomy, and behavioral strategies will help select, structure, and create learning environments. Cell phone activities/operations such as alarm, calendar, and timer may be categorized into strategies relating to self-instruct and self-monitor. Similarly, notes and Google Docs may be categorized into strategies for selecting, structuring, and creating learning environments. In addition, defining and categorizing CPU activities/operations/cell phone Apps such may help quantify and measure the targeted behavior related to health, mood, exercise, eating habits, social activities, and academic performance. Such an App may also help measure the determinants of Bandura's triadic model such

as judgment of one's behavior and environmental circumstances, which may guide academics, researchers, and policymakers to define, categorize, and quantify SRL behaviors/processes.

More research is needed to explore the ways digital technology like cell phones can help regulate learning processes. Also, a study assessing the impact of CPU on academic performance during unprecedented times like the COVID-19 pandemic ("Coronavirus disease 2019 (COVID-19)," 2020) is warranted when virtual educational platforms (Teams, Zoom, Cisco WebEx, Hangout, etc.) are used to lead instruction in higher education classrooms.

Recommendations

Both subjective and objective measures should be used to gain a detailed, comprehensive, and in-depth understanding of CPU variables. The cell phone operating system records (i.e., real-time classroom cell phone switching, social interaction, mobility, and learning theory-based CPU apps) could be used to better understand CPU behaviors. Moreover, these measures should rely on self-regulation mechanisms built on the "learning process" rather than "learning behaviors." Diverse and representative 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 or CPU activities/operations to existing theories will always help provide a theoretical basis for CPU research. Having a study done to determine if quarantine has impacted CPU, multitasking, and the use of learning theory-based CPU is warranted.

Appendices

Appendix A. Scale reliability

Various measures were taken to test the scale reliability. The Kaiser–Meyer–Olkin (KMO) measures of sampling adequacy were administered to see the loading of the items within the constructs. All ten items from the construct of CPU_Multitasking ($KMO = 0.89$, $p < 0.001$) and all nine items from the construct of CPU_SRLBehavior ($KMO = 0.78$, $p < 0.001$) loaded well within the constructs, as determined by the KMO measures. 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 both constructs were statistically significant ($p < 0.001$). 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 items in the instrument were found to exhibit good internal consistency [Cronbach's $\alpha = 0.90$ (spring 2019 study); Cronbach's $\alpha = 0.83$ (fall 2019 study)] in both pilot studies.

Appendix B.1. CPU_Multitasking measures

Ten items were used to measure the frequency of switching back and forth between cell phones and academic tasks during a class/lecture, lab, and/or study session on a ratio-based scale from 0 to 40. The ratio-based scale allowed participants to indicate a number that was accurate for them. The average of the scores provided a total score for CPU_Multitasking. The items related to classroom CPU were adapted from Li et al. (2015), Elder (2013), and Bjornsen and Archer (2015). The list of classroom cell phone activities was extracted from previous studies (Berry & Westfall, 2015; Bjornsen & Archer, 2015; Braguglia, 2011; Elder, 2013; Li et al., 2015). Items based on a particular cell phone activity (such as texting, emailing, social networking, and checking reminders) were further modified to make them more suitable for 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 modification was made to the following CPU activities: texting, commercial/promotional, social media, emails, reminders, and surfing the internet.

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." Bjornsen and Archer (2015) used four items to assess the use of cell phones in the 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 CPU 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).

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 to 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/lecture, lab, and/or study session for various cell phone activities, such as texting, emailing, social networking, surfing the internet, checking reminders, and checking notifications. 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-min 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 – 40 times)?, (ii) During a 60-min 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 – 40 times)?.

The validity of adapted items was tested in the respective source studies. For example, the validity of CPU classroom items was tested by Elder (2013), and the items possessed good internal consistency (Cronbach’s alpha = 0.75). The validity of CPU classroom items adapted from Li et al. (2015) was also well tested and items exhibited good internal consistency (Cronbach’s a = 0.74).

The final CPU_Multitasking items were as follows:

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

1. check your cell phone for text messages (including instant messages) and read them
0 times40 times
2. use your cell phone to write a reply to a text message
0 times40 times
3. check your cell phone for commercial notifications such as promotional offers (shopping, banking, etc.)
0 times40 times
4. respond to commercial notifications such as promotional offers (shopping, banking, etc.) using your cell phone
0 times40 times
5. check your cell phone for social media (Instagram, Twitter, Snapchat, Facebook, LinkedIn, etc.) notifications
0 times40 times
6. use your cell phone to write (or to respond to) messages on social media (Instagram, Twitter, Snapchat, Facebook, LinkedIn, etc.)
0 times40 times
7. check your emails using your cell phone
0 times40 times

8. use your cell phone to write (or to respond to) emails
0 times40 times
9. check your cell phone for any type of reminders (calendar, meeting alerts, alarms, timers etc.)
0 times40 times
10. use your cell phone for surfing the Internet (for academic or non-academic purposes)
0 times40 times

Appendix B.2. CPU_SRLBehavior measures

Nine items were used to measure the use of cell phones for SRL 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 assessed CPU for SRL behaviors on a daily basis. The average of the items provided a total score for CPU_SRLBehavior.

CPU_SRLBehavior items were adapted from previous studies. A self-efficacy scale for SRL (Cronbach’s alpha = 0.87) was used as a reference scale for all the items (Zimmerman et al., 1992). 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 (2011) 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).

Concerning the psychometric properties, the instrument used by Han and Yi (2018) 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 final CPU_SRLBehavior items were as follows:

On a daily basis, how often do you use your cell phone to.

1. use an alarm to regulate sleeping/waking-up

Never Occasionally Often Always

2. use a calendar to indicate important dates, set goals, or keep a schedule

Never Occasionally Often Always

3. use notes to write strategies, monitor progress, or evaluate yourself

Never Occasionally Often Always

4. use a timer, stopwatch, or clock function to adhere to a study schedule

Never Occasionally Often Always

5. use a search engine or another learning tool to obtain course information (Google search, eCampus, Black-Board etc.)

Never Occasionally Often Always

6. use Google Docs, etc. to review, rehearse, or revise class notes

Never Occasionally Often Always

7. use email or social media to seek peer, teacher, or any other academic assistance

Never Occasionally Often Always

8. use text messaging to clarify information, collaborate with peers, or get quick answers

Never Occasionally Often Always

9. use a calculator to complete mathematical functions related to an assignment

Never Occasionally Often Always

Appendix C

Table 4 The descriptive statistics of CPU_Multitasking and CPU_SRLBehavior on sex, ethnicity, year in college, and college

Variable	Group	CPU_Multitasking		CPU_SRLBehavior	
		Mean ± SD	<i>p</i> value	Mean ± SD	<i>p</i> 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	

CPU_Multitasking=The frequency of cell phone use during a class/lecture, lab and/or study session, CPU_SRLBehavior=The use of cell phones for self-regulated learning behavior

p* < 0.05, *p* < 0.001

Table 5 The cell phone use of undergraduate students for self-regulated learning behavior among variable sex

CPU Activity	CPU_SRLBehavior			
	Sex			
	Female (Mean ± SD)	Male (Mean ± SD)	<i>p</i> 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	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

CPU = Cell Phone Use, CPU_SRLBehavior = The use of cell phones for self-regulated learning behavior, N.S. = Not statistically significant

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

Table 6 The cell phone use of undergraduate students for self-regulated learning behavior among ethnicity

CPU Activity	CPU_SRLBehavior				<i>p</i> value	Effect Size
	Ethnicity					
	African American (Mean ± SD)	Latinx (Mean ± SD)	Caucasian (Mean ± SD)	Asian (Mean ± SD)		
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	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

CPU = Cell Phone Use, CPU_SRL = The use of cell phones for self-regulated learning behavior, N.S. = Not statistically significant

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

Data availability Not applicable.

Declarations

Ethical committee permission This study was reviewed and approved by the Institutional Review Board (IRB) (IRB2019-0980 M) under the 45 CFR 46.104 declaration of the Human Research Protection Program (HRPP) of the University. All the procedures in the study involving human participants were performed in accordance with the IRB and HRPP standards.

Informed consent An informed consent was obtained from all the participants included in the study.

Conflicting interests The author(s) report no conflict of interest.

References

- Abernethy, M. (2015). Self-reports and observer reports as data generation methods: An assessment of issues of both methods. *Universal Journal of Psychology*, 3(1), 22–27. <https://doi.org/10.13189/ujp.2015.030104>
- Adler, R. F., & Benbunan-Fich, R. (2013). Self-interruptions in discretionary multitasking. *Computers in Human Behavior*, 29(4), 1441–1449. <https://doi.org/10.1016/j.chb.2013.01.040>
- Alessandrini, V. (2015). *Shared memory application programming: Concepts and strategies in Multicore application programming* (1st ed.). Morgan Kaufmann Publishers.
- Alvarez-Risco, A., Estrada-Merino, A., Anderson-Seminario, M. D., Młodzianowska, S., García-Ibarra, V., Villagomez-Buele, C., & Carvache-Franco, M. (2020). Multitasking behavior in online classrooms and academic performance: Case of university

- students in Ecuador during COVID-19 outbreak. *Interactive Technology and Smart Education*, 18(3), 422–434. <https://doi.org/10.1108/itse-08-2020-0160>
- Amez, S., & Baert, S. (2020). Smartphone use and academic performance: A literature review. *International Journal of Educational Research*, 103, 101618. <https://doi.org/10.1016/j.ijer.2020.101618>
- Annoni, A. M., Petrocchi, S., Camerini, A., & Marciano, L. (2021). The relationship between social anxiety, smartphone use, dispositional trust, and problematic smartphone use: A moderated mediation model. *International Journal of Environmental Research and Public Health*, 18(5), 2452. <https://doi.org/10.3390/ijerph18052452>
- Asamoah, T. (2020). *Digital overload: What is it, and how is it affecting our mental and physical health?* Retrieved August 7, 2021, from <https://www.goodrx.com/blog/what-is-digital-overload-definition-symptoms-how-to-manage/>
- Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational Behavior and Human Decision Processes*, 50(2), 248–287. [https://doi.org/10.1016/0749-5978\(91\)90022-1](https://doi.org/10.1016/0749-5978(91)90022-1)
- 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. <https://doi.org/10.1080/87567555.2015.1005040>
- Bethlehem, J., & Biffignandi, S. (2011). *Handbook of web surveys*. John Wiley & Sons Inc.
- 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. <https://doi.org/10.1037/stl0000045>
- Blasiman, R. N., Larabee, D., & Fabry, D. (2018). Distracted students: A comparison of multiple types of distractions on learning in online lectures. *Scholarship of Teaching and Learning in Psychology*, 4(4), 222–230. <https://doi.org/10.1037/stl0000122>
- Boumosleh, J. M., & Jaalouk, D. (2017). Depression, anxiety and smartphone addiction in university students—A cross-sectional study. *PLoS ONE*, 12, e0182239.
- Braguglia, K. H. (2011). Cellular telephone use: A survey of college business students. *Journal of College Teaching & Learning (TLC)*, 5(4). <https://doi.org/10.19030/tlc.v5i4.1279>
- Chen, Q., & Yan, Z. (2016). Does multitasking with mobile phones affect learning? A review. *Computers in Human Behavior*, 54, 34–42. <https://doi.org/10.1016/j.chb.2015.07.047>
- Chen, R. S., & Ji, C. H. (2015). Investigating the relationship between thinking style and personal electronic device use and its implications for academic performance. *Computers in Human Behavior*, 52, 177–183.
- Chen, Y., & Peng, S. (2008). University students' internet use and its relationships with academic performance, interpersonal relationships, psychosocial adjustment, and self-evaluation. *Cyber Psychology and Behavior*, 11, 467–469. <https://doi.org/10.1089/cpb.2007.0128>
- Cleary, P. D. (1997). Subjective and objective measures of health: Which is better when? *Journal of Health Services Research & Policy*, 2(1), 3–4. <https://doi.org/10.1177/135581969700200102>
- Coronavirus disease 2019 (COVID-19). (2020). Retrieved April 7, 2020, from <https://www.cdc.gov/coronavirus/2019-ncov/index.html>
- Couper, M. P. (2008). *Designing effective web surveys*. Cambridge University Press.
- Demirci, K., Akgönül, M., & Akpınar, A. (2015). Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. *Journal of Behavioral Addictions*, 4(2), 85–92. <https://doi.org/10.1556/2006.4.2015.010>
- Demographics of mobile device ownership and adoption in the United States*. (2021, April 26). Pew Research Center: Internet, Science & Tech. Retrieved May 3, 2021, from <https://www.pewresearch.org/internet/fact-sheet/mobile/>
- De-Sola Gutiérrez, J., Rodríguez de Fonseca, F., & Rubio, G. (2016). Cell-phone addiction: A review. *Frontiers in Psychiatry*, 7. <https://doi.org/10.3389/fpsy.2016.00175>
- Drost, E. (2011). Validity and reliability in social science research. *Education Research and Perspectives*, 38(1), 105–123.
- Durlak, J. A. (2009). How to select, calculate, and interpret effect sizes. *Journal of Pediatric Psychology*, 34(9), 917–928. <https://doi.org/10.1093/jpepsy/jsp004>
- Elder, A. D. (2013). College students' cell phone use, beliefs, and effects on their learning. *College Student Journal*, 47(4), 585–592.
- Felisoni, D. D., & Godoi, A. S. (2018). Cell phone usage and academic performance: An experiment. *Computers & Education*, 117, 175–187. <https://doi.org/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.
- Fox, J., & Monette, G. (1992). Generalized collinearity diagnostics. *Journal of the American Statistical Association*, 87(417), 178–183. <https://doi.org/10.1080/01621459.1992.10475190>
- 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. <https://doi.org/10.1177/0098628313514177>
- Green, L., & Celkan, G. (2014). A very crucial turning point in one's life: College/University choice. *Procedia - Social and Behavioral Sciences*, 116, 990–995. <https://doi.org/10.1016/j.sbspro.2014.01.333>
- 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. <https://doi.org/10.1111/jcal.12306>
- Hartley, K., Bendixen, L. D., Gianoutsos, D., & Shreve, E. (2020). The smartphone in self-regulated learning and student success: Clarifying relationships and testing an intervention. *International Journal of Educational Technology in Higher Education*, 17(1). <https://doi.org/10.1186/s41239-020-00230-1>
- Hawi, N. S., & Samaha, M. (2017). The relations among social media addiction, self-esteem, and life satisfaction in university students. *Social Science Computer Review*, 35(5), 576–586. <https://doi.org/10.1177/0894439316660340>
- Hitlin, P. (2020). *Use of internet, social media, digital devices plateau in US*. Pew Research Center. Retrieved May 3, 2021, from <https://www.pewresearch.org/fact-tank/2018/09/28/internet-social-media-use-and-device-ownership-in-u-s-have-plateaued-after-years-of-growth/>
- Ho, R. C., Zhang, M. W. B., Tsang, T. Y., Toh, A. H., Pan, F., Lu, Y., et al. (2014). The association between internet addiction and psychiatric co-morbidity: A meta-analysis. *BMC Psychiatry*, 14, 183.
- 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. <https://doi.org/10.1016/j.chb.2012.06.020>
- 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.
- Joshi, S. C. (2022). Sleep latency and sleep disturbances mediates the association between nighttime cell phone use and psychological well-being in college students. *Sleep and Biological Rhythms*, 20, 431–443. <https://doi.org/10.1007/s41105-022-00388-3>
- Joshi, S. C., Woodward, J., & Woltering, S. (2021). Nighttime cell phone use and sleep quality in young adults. *Sleep and*

- Biological Rhythms*, 20(1), 97–106. <https://doi.org/10.1007/s41105-021-00345-6>
- Junco, R., & Cotten, S. R. (2012). No A 4 U: The relationship between multitasking and academic performance. *Computers & Education*, 59(2), 505–514. <https://doi.org/10.1016/j.compedu.2011.12.023>
- Kelly, R. (2017). *Survey: 94% of students want to use their cell phones in class -- Campus technology*. Campus Technology. Retrieved August 1, 2021, from <https://campustechnology.com/articles/2017/12/12/students-want-to-use-their-cell-phones-in-class.aspx>
- Kim, M., Kim, I., & Lee, U. (2021). Beneficial neglect: Instant message notification handling behaviors and academic performance. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 5(1), 1–26. <https://doi.org/10.1145/3448089>
- Kocak, O., Goksu, I., & Goktas, Y. (2021). The factors affecting academic achievement: a systematic review of meta analyses. *International Online Journal of Education and Teaching (IOJET)*, 8(1), 454–484.
- Kumcagiz, H., & Gunduz, Y. (2016). Relationship between psychological well-being and smartphone addiction of university students. *International Journal of Higher Education*, 5(4). <https://doi.org/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, S. J., Kim, Y., & Kwak, Y. (2020). Influence of smartphone addiction and poor sleep quality on attention-deficit hyperactivity disorder symptoms in university students: A cross-sectional study. *Journal of American College Health*, 1–7. <https://doi.org/10.1080/07448481.2020.1740228>
- 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. <https://doi.org/10.3389/fpsyg.2013.00863>
- Le Roux, D. B., & Parry, D. A. (2021). An exploratory investigation of the use and effects of academic instant messaging groups among university students. *Education and Information Technologies*. <https://doi.org/10.1007/s10639-021-10631-y>
- 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. <https://doi.org/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. <https://doi.org/10.1016/j.chb.2015.06.021>
- Lin, Y., Liu, Y., Fan, W., Tuunainen, V. K., & Deng, S. (2021). Revisiting the relationship between smartphone use and academic performance: A large-scale study. *Computers in Human Behavior*, 122, 106835. <https://doi.org/10.1016/j.chb.2021.106835>
- Lisewski, T., Sweeney, D., Miele-Moran, C., Osman, F., Cavaliere, C., & Damiao, J. (2020). Smartphone addiction and its effects on sophomore college students' grade point averages. *American Journal of Occupational Therapy*, 74(4_Supplement_1), 7411505112p1. <https://doi.org/10.5014/ajot.2020.74s1-p2513>
- Mark, G., Gudith, D., & Klocke, U. (2008). The cost of interrupted work. *Proceeding of the twenty-sixth annual CHI conference on Human factors in computing systems - CHI '08*. <https://doi.org/10.1145/1357054.1357072>
- Mark, G., Wang, Y., & Niiya, M. (2014). Stress and multitasking in everyday college life: an empirical study of online activity. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 41–50. <https://doi.org/10.1145/2556288.2557361>
- Massey, Z. B., Brockenberry, L. O., & Harrell, P. T. (2021). Vaping, smartphones, and social media use among young adults: Snapchat is the platform of choice for young adult vapers. *Addictive Behaviors*, 112, 106576. <https://doi.org/10.1016/j.addbeh.2020.106576>
- 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. <https://doi.org/10.1016/j.chb.2018.04.027>
- Meyer, J., McDowell, C., Lansing, J., Brower, C., Smith, L., Tully, M., & Herring, M. (2020). Changes in physical activity and sedentary behaviour due to the COVID-19 outbreak and associations with mental health in 3,052 US adults. <https://doi.org/10.33774/coe-2020-h0b8g>
- Nayak, J. K. (2018). Relationship among smartphone usage, addiction, academic performance and the moderating role of gender: A study of higher education students in India. *Computers & Education*, 123, 164–173. <https://doi.org/10.1016/j.compedu.2018.05.007>
- 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. <https://doi.org/10.1177/0098628316677913>
- 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. <https://doi.org/10.1089/cyber.2011.0580>
- Pera, A. (2020). The psychology of addictive smartphone behavior in young adults: Problematic use, social anxiety, and depressive stress. *Frontiers in Psychiatry*, 11. <https://doi.org/10.3389/fpsyg.2020.573473>
- Perrin, A., & Atske, S. (2021). *About three-in-ten U.S. adults say they are 'almost constantly' online*. Pew Research Center. Retrieved July 7, 2021, from <https://www.pewresearch.org/fact-tank/2021/03/26/about-three-in-ten-u-s-adults-say-they-are-almost-constantly-online/>
- 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, Internet & Technology; Americans and their cell phones. (2011). Retrieved from <http://www.pewinternet.org/2011/08/15/americans-and-their-cell-phones/>
- Roberts, J., Yaya, L., & Manolis, C. (2014). The invisible addiction: Cell-phone activities and addiction among male and female college students. *Journal of Behavioral Addictions*, 3(4), 254–265. <https://doi.org/10.1556/jba.3.2014.015>
- 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.
- Rugutt, J. K., & Chemosit, C. C. (2005). A study of factors that influence college academic achievement: A structural equation modeling approach. *Journal of Educational Research & Policy Studies*, 5(1), 66–90.
- Sapci, O., Elhai, J. D., Amialchuk, A., & Montag, C. (2021). The relationship between smartphone use and students' academic performance. *Learning and Individual Differences*, 89, 102035. <https://doi.org/10.1016/j.lindif.2021.102035>
- Seilhamer, R., Chen, B., Bauer, S., Salter, A., & Bennett, L. (2018, April 23). *Changing mobile learning practices: A Multiyear study 2012–2016*. EDUCAUSE Review | EDUCAUSE. Retrieved August 1, 2021, from <https://er.educause.edu/articles/2018/4/>

[changing-mobile-learning-practices-a-multiyear-study-2012-2016#fn4](#)

- Sohn, S. Y., Krasnoff, L., Rees, P., Kalk, N. J., & Carter, B. (2021). The association between smartphone addiction and sleep: A UK cross-sectional study of young adults. *Frontiers in Psychiatry, 12*. <https://doi.org/10.3389/fpsy.2021.629407>
- Sönmez, M., Gürlek Kısacık, Ö., & Eraydın, C. (2020). Correlation between smartphone addiction and loneliness levels in nursing students. *Perspectives in Psychiatric Care, 57*(1), 82–87. <https://doi.org/10.1111/ppc.12527>
- Stewart, A. L., Thrasher, A. D., Goldberg, J., & Shea, J. A. (2012). A framework for understanding modifications to measures for diverse populations. *Journal of Aging and Health, 24*(6), 992–1017. <https://doi.org/10.1177/0898264312440321>
- 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. <https://doi.org/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](https://dars.tamu.edu/Student/Preliminary-Enrollment-(1)?_ga=2.152189049.1917902325.1585590429-1828266557.1558703200)
- Thomé, 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). <https://doi.org/10.1186/1471-2458-10-66>
- Time spent on average on a smartphone in the U.S. 2021*. (2021). Statista. Retrieved July 7, 2021, from <https://www.statista.com/statistics/1224510/time-spent-per-day-on-smartphone-us/>
- 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. <https://doi.org/10.1080/87567555.2011.604802>
- 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. <https://doi.org/10.1111/bjet.12176>
- Troll, E. S., Friese, M., & Loschelder, D. D. (2021). How students' self-control and smartphone-use explain their academic performance. *Computers in Human Behavior, 117*, 106624. <https://doi.org/10.1016/j.chb.2020.106624>
- Usher, E. L., & Schunk, D. H. (2018). Social cognitive theoretical perspective of self-regulation. In D. H. Schunk & J. A. Greene (Eds.), *Handbook of self-regulation of learning and performance* (2nd ed., pp. 35–51). Routledge. <https://doi.org/10.4324/9781315697048>
- Uzun, A. M., & Kilis, S. (2019). Does persistent involvement in media and technology lead to lower academic performance? Evaluating media and technology use in relation to multitasking, self-regulation and academic performance. *Computers in Human Behavior, 90*, 196–203. <https://doi.org/10.1016/j.chb.2018.08.045>
- Wheelwright, T. (2021). *Cell phone behavior survey: Are people addicted to their phones?* reviews.org. Retrieved July 7, 2021, from <https://www.reviews.org/mobile/cell-phone-addiction/>
- 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-realist-possibility/74312.html>
- Yot-Domínguez, C., & Marcelo, C. (2017). University students' self-regulated learning using digital technologies. *International Journal of Educational Technology in Higher Education, 14*(38). <https://doi.org/10.1186/s41239-017-0076-8>
- Yuan, G., Elhai, J. D., & Hall, B. J. (2021). The influence of depressive symptoms and fear of missing out on severity of problematic smartphone use and internet gaming disorder among Chinese young adults: A three-wave mediation model. *Addictive Behaviors, 112*, 106648. <https://doi.org/10.1016/j.addbeh.2020.106648>
- Zhang, M. W. B., Ho, C. S. H., & Ho, C. M. (2014). Methodology of development and students' perceptions of a psychiatry educational smartphone application. *Technology and Health Care, 22*, 847–855.
- Zimmerman, B. J. (1986). Becoming a self-regulated learner: Which are the key subprocesses? *Contemporary Educational Psychology, 11*, 307–313. [https://doi.org/10.1016/0361-476x\(86\)90027-5](https://doi.org/10.1016/0361-476x(86)90027-5)
- Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology, 81*, 329–339. <https://doi.org/10.1037/0022-0663.81.3.329>
- 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., & Moylan, A. R. (2009). Self-regulation: where metacognition and motivation intersect. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Handbook of metacognition in education* (pp. 299–315). Routledge.
- 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. <https://doi.org/10.2307/1163261>

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