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A positive view of excessive smartphone utilization and its relationship with other academic-related variables within the online course setting

Abstract

The continual use of smartphones is a global problem that requires scholars' attention. This study investigates the impact of excessive smartphone use, self-regulation, and procrastination on students' online academic performance. A total of $n = 238$ university students participated in the study. Mean comparisons unveiled clear discrepancy scores on procrastination, self-regulation, and daily hours spent on smartphones between the smartphone-addicted and non-addicted students. Structural Equation Modeling helps us to answer our hypothesis. Unusually, smartphone use had a significant and positive effect on online students' academic performance. Also, the study provides a better understanding of the procrastination factor that significantly impacts students' smartphone use and online academic performance. Results are discussed considering possible interventions at the academic level.

Keywords: Smartphone use, self-regulation, procrastination, Grade Point Average, UAE

Word count: 7528 words

1. Introduction

The dawn of the digital age is characterized by two important moments: the demise of mobile phones in favor of smartphones and the use of smartphones as personal computers. Companion to humans, smartphones are multifaceted tools that occupy a unique place in our everyday life. The United Arab Emirates (UAE) accounts for 90% of smartphone owners, and the remaining respondents, 70% of them, claim that they will buy a smartphone (YouGov, 2018). Also, UAE residents aged between 18 and 29 spend 7 hours daily using their smartphones (YouGov, 2018). A similar result is found in a more recent survey conducted by Statista (2023); specifically, around 97.6% of people in the UAE are using smartphones in 2021. Also, a recent study has confirmed the increased number of smartphone users and its problematic nature within the UAE (Ameen, Willis and Shah, 2018). More than a simple distraction when doing different activities such as watching TV, working, or dining in a restaurant with friends, its use is now a synonym of addiction. Smartphones are now considered inseparable companions (Lepp et al. 2015). In the YouGov (2018) study for the UAE, 76% of the respondents admitted to looking at their phone frequently, while 72% claimed to reach for their device first thing in the morning.

The use of a smartphone can be a double-edged sword. As mentioned, its use may become rather addictive very quickly. Nevertheless, it is a technological advance that has made everything reachable through touch, such as ordering groceries, organizing video calls with your loved ones, entertaining while having free time, reading books and journals, and having access to many applications that enable those activities during the pandemic. But the border between the benefits and limitations of smartphone use is relatively blurry where the use of smartphones can become dangerously addictive. It is well known that constant smartphone usage impacts sleeping habits, fosters stress and anxiety, and dampens academic performance and physical activity

(Thomé et al., 2011; Yang et al., 2019). Smartphone addiction is not country-specific; a recent study has shown a cross-cultural effect (Panek et al., 2018).

Studies have considered the idea of excessive use of smartphones as a “problematic use” leading to dependence or addiction (e.g., Hussain et al., 2017; Yang et al., 2019). The COVID-19 pandemic has led people to use their phone more extensively than normal (Sebir, 2020). The excessive use of smartphones is considered an addiction and, more precisely, a non-substance addiction as psychiatrically diagnosed by professionals. Nonetheless, we believe “smartphone use” is forceful enough to fulfill the study’s objective; for example, we used “hours spent on smartphones” as an indicator as suggested by scholars (Domoff, Foley, and Ferkel, 2020).

To strengthen our knowledge of excessive smartphone use in an online academic setting, this study examines the relationship between smartphone use, self-regulation, academic performance, and procrastination. Although the use of smartphones in academic performance has been discussed in previous studies (e.g., Amez and Baert, 2020), much less is known about the impact that addictive smartphone use may have on academic performance (Domoff, Foley, & Ferkel, 2020). Apart from a few exceptions (Felisoni & Godoi, 2018; Giunchiglia, Zeni, Gobbi, Bignotti, & Bison, 2018), this study contributes further to this limited body of knowledge in at least two ways.

First, we investigate this relationship in the Middle East region which critically lacks such studies (Alotaibi et al., 2022), especially when smartphone use is known to have increased remarkably in the Middle East region over the past decade based on a recent report by YouGov (2018). Second, in line with recommendations to further examine the impact of smartphone addiction in the academic field (Domoff, Foley, & Ferkel, 2020), this study explored age and gender as essential covariation factors between self-regulation and procrastination. Moreover,

this research will indirectly explore the direct impact of self-regulation and procrastination on academic performance through smartphone use. The role of procrastination relates to the act of delaying academic work (Gustavson & Miyake, 2017; Kertechian, 2018) while self-regulation involve the ability of students to manage their own behavior and emotions (Bidjerano & Dai, 2007; Dörrenbächer & Perels, 2016; Eilam et al., 2009) – both concepts are well documented in academic settings.

Besides, one can note that the UAE is the most digital-friendly country in the Middle East (Euler Hermes, 2018). Coupled with the fact that research on smartphone use within the academic context is yet to be explored in that area, we provide a solid ground for the present study's narrative (see figure 1). This study has several implications for providing scholars with detailed predictions on how some variables might foster or negatively impact academic performance, and ultimately aims to assist university counselors in building personalized interventions strategies for students such as training or seminars/webinars.

This paper focuses on the context of “academic online settings” regardless of other environmental factors. Although the data for this study may have been collected during the COVID-19 pandemic, it is worth noting that the authors are in no way inferring that the COVID-19 pandemic has stimulated online learning. The online learning environment has been active long before the pandemic with many universities embracing online learning more than a decade ago. This is the case of University of the People, for example, which is a fully online institution recognized by the American Distance Education Accrediting Commission (DEAC). While this example represents an entirely online institution, major universities in the world offer fully online certificates, diplomas, and degrees as well. The choice to embrace an online setting is

strategic- it existed before the pandemic and early discussions of this concept date back to the 2000s' (Harasim, 2000).

In this paper, we aim at analyzing the importance of smartphones, its uses, and regulations within the UAE academic ecosystem as a unique contribution of this study. Therefore, classical relationships (e.g. smartphone use and GPA) have been investigated in the context of the UAE and in an online learning setting.

2. Literature Review

2.1. Smartphone Use and Academic Performance

A recent systematic review demonstrated a negative association between students' frequency of smartphone use and their academic performance (Amez & Baert, 2020), and this inference holds true during the COVID-19 pandemic (Albursan et al., 2022) as well as in post-COVID situations in Asia (Yao & Wang, 2022; Iqbal et al., 2021) and the Middle-east (Alotaibi et al., 2022). While academic performances are negatively impacted by the extensive use of smartphones, the whole learning process is also weakened (Sunday, Adesope, & Maarhuis, 2021). Specifically, "possessing a smartphone" is a strong and positive conjecture among people aged 18–29, potentially representing many students. A more fine-tuned perspective led us to add that individuals engaging in study-related excessive use of their smartphones tend to achieve higher academic results, whereas game-related usage would negatively affect academic outcomes (Abbasi et al., 2021).

The COVID-19 pandemic irremediably accelerated the establishment of online teaching to become the new teaching standard among universities. While in-class instruction would have been preventing smartphone use, being at home reinforces its use. Research has found a negative impact of smartphone use on aspects of health such as sleep quality (Christensen et al., 2016;

Demirci et al., 2015; Rosen et al., 2016), mental health, and physical fitness (Lepp et al., 2015). Concomitantly, academic performance is, in turn impacted by the weakening of these health indicators (Baert et al., 2015; Galambos et al., 2013).

Beyond the impact of smartphone use on students' health conditions, it impacts students' ability to concentrate during class. While most of the studies have been conducted in an actual class session, we expect to find a similar and even stronger negative relationship between smartphone use and online academic performance (Junco & Cotten, 2012; Levine et al., 2012). The literature has identified four main reasons explaining such a relationship. First, multitasking in smartphones is a common feature that negatively impacts academic performance (Karpinski et al., 2013; Rosen et al., 2013). Second, smartphone features such as notifications may distract students during class or coursework (Junco & Cotten, 2012), which is another reason why students get distracted by their smartphones relating to the fear of missing out (i.e., "FOMO"); in other words, students feel the need to know about the latest news as soon as it is sent out, thus impacting students' academic performance (Chen & Yan, 2016). Third, students' online presence on social networks interferes with studying (Vitak et al., 2011). Fourth, students may feel unmotivated towards studying, and smartphones then represent a way to escape academic boredom (Hawi & Samaha, 2017). The Middle East and particularly the UAE are no exception, a priori, to this framework, thus:

H1. The over usage of smartphones among students in the UAE would exacerbate its relationship with academic performance, so that this relationship is negative.

2.2. Self-Regulation

Moving from a physical in-class setting to an online environment has undeniably affected university students. This transition, which can be seen as a process, needs to be fully embraced

by students to maintain a certain academic level. Parallelism is found with self-regulation, described as “those processes, internal and transactional, that enable an individual to guide his/her goal-directed activities over time and across changing circumstances (contexts)” (Karoly, 1993, p. 25). Thus, students who can engage successfully in self-regulation tend to be less smartphone-addicted, while students who fail to express self-regulation will be more likely smartphone-addicted and are more likely to undergo well-being issues (Soror et al., 2012). If such association has been established in the European context (Gökçearsan et al., 2016; van Deursen et al., 2015), it remains crucial to clarify this association among UAE university students. Thus, we envision the following hypothesis:

H2. UAE students who are incapable of focusing on academic activities through self-regulations processes would have a higher tendency to use their smartphones.

Failure in educational self-regulation has been associated with procrastination (Hosseini & Khayyer, 2009; Özer et al., 2009). Naturally, high self-regulators tend to finalize their course work on time (Darling-Hammond et al., 2020). Rahmani Javanmard and Mohammadi (2017) suggested that fear of failure was a positive predictor of academic procrastination. Mohsenzadeh et al. (2016) established that high-school students’ personality characteristics associated with fear of failure were significantly related to academic procrastination. One study found that conscientiousness was negatively associated with procrastination, confirming its highly recognized positive effects on academic-related outcomes (Kertechian 2018). To the best of our knowledge, educational self-regulation’s association with procrastination is not well understood, while other factors, such as fear of failure, have been widely studied (Mohsenzadeh et al. 2016; Rahmani & Mohammadi 2017). Then, the analysis of the association between self-regulation and procrastination requires more attention. Thus, we hypothesize the following:

H3. If students cannot show a high level of self-regulation that incorporates the ability to adapt to new settings, then their procrastination level will increase.

Scholars have persistently associated self-regulation as a strong predictor of academic performance (Bidjerano and Dai 2007; Dörrenbächer and Perels 2016; Eilam, Zeidner, and Aharon 2009). In Pakistan, for example, self-regulation has been identified as an antecedent of academic performance and this relationship is even stronger with the presence of a positive use of academic social networking sites (Iqbal et al., 2021). Within self-regulation, “effort regulation” in learning seems to be a robust predictor for academic performance (Richardson et al., 2012; Sitzmann & Ely, 2011) and academic achievement (Estévez et al., 2021). In other studies, self-regulation appeared to be a mediator fostering academic performance, between contextual characteristics and academic performance (Pintrich, 2004) and between self-efficacy and academic performance (Komarraju & Nadler, 2013). In a more recent study conducted during the COVID-19 pandemic, self-directed learning was a predictor of academic achievement (Yavuzalp & Bahcivan, 2021). The online learning setting forced universities to adapt to changes quickly, thus we hypothesize the following:

H4. Students who can self-regulate in time of change have less difficulties in obtaining a higher GPA.

2.3. Academic Procrastination

Over the last decade, procrastination has been defined several times. Klingsieck (2013) suggested a unified definition of procrastination as “the voluntary delay of an intended and necessary and [personally] important activity, despite expecting potential negative consequences that outweigh the positive consequences of the delay.” (Klingsieck, 2013, p. 26). Moreover, procrastination is mostly present among students (Eerde, 2003; Schouwenburg et al., 2004) and

needs to be overcome to ensure a certain level of success and happiness in life (Steel, 2007). Correspondingly, academic procrastination would be defined as postponing academic-related activities such as coursework (Kandemir, 2014; Schouwenburg et al., 2004). This phenomenon is quite common as half of the students engage in procrastination (Özer et al., 2009), and this estimation appears to increase (Steel, 2007). Thus, procrastination remains an exciting topic of investigation among students, especially when analyzing its association with academic performance.

A recent meta-analysis from Kim & Seo (2015) has identified inconsistent results between procrastination and academic performance. For example, procrastination hurts learning and achievement (Aremu et al., 2011; Balkis, 2013). Within the procrastination framework, time is seen as a pressure that participates in lowering accuracy and punctuality. Based on this, it is argued that procrastination will negatively impact academic performance (Eerde, 2003). Other studies have found an absence of a relationship between procrastination and academic performance (Odaci, 2011; Solomon & Rothblum, 1984) and sometimes a positive relationship (Brinthaupt & Shin, 2001; Schraw et al., 2007). Ferrari et al. (1995) stated that students with higher ability tend to be more procrastinators than those with lower ability. Nevertheless, two recent studies confirmed the negative relationship (Gustavson & Miyake, 2017; Kertechian, 2018). Furthermore, studies have also established that procrastination is a mediator between Instagram addiction and academic performance, whereby the relationship became negative in the presence of procrastination (Pekpazar et al., 2021). As confirmed in previous studies, we similarly hypothesize the following among UAE students:

H5. A high level of procrastination among UAE students leads to lower GPA.

Procrastination is an older concept than the use of the smartphone. Moreover, we believe that procrastination emerged as a predictor of smartphone use. Indeed, students might be distracted by their smartphones when they engage in academic procrastination (e.g., postponing an assignment). While studies have been interested in predicting general procrastination and have found a positive relationship with internet addiction (Geng et al., 2018; Rozgonjuk et al., 2018; Ryan et al., 2016), we aim to identify academic procrastination as a predictor of smartphone use. To the best of our knowledge, there is a lack of empirical evidence on the relationship between academic procrastination and smartphone use. Thus, we propose the following:

H6. UAE students who postpone their academic work have a higher tendency to use their smartphone than their counterpart with lower level of procrastination.

3. Methodology

3.1. Participants

Data were collected from 238 students following a convenience sampling method. At the time of the survey, between January 10th, 2021, and February 10th, 2021, students were registered in a wide range of academic majors in a university located in Downtown Dubai, United Arab Emirates.

3.2. Procedure

Data were collected by sending emails to students regularly registered at the University. The email template was composed of an explanation text and a link to redirect students to the questionnaire. Students were reminded of a few important pieces of information such as the opportunity to leave the questionnaire at any time, the anonymity of their responses (i.e., emails and names were not requested), the shortness of the present questionnaire (i.e., not more than 10

minutes), and that only the researcher in charge of the present study could access the data and analyze them.

3.3. Instruments

The survey package includes items directly taken from already available questionnaires, developed by scholars and used several times in similar topic research. This applies to the self-regulation questionnaire (Gökçearsan et al., 2016; Yang et al., 2019), the smartphone addiction questionnaire (Rozgonjuk et al., 2018; Yang et al., 2019), and the procrastination questionnaire (Brando-Garrido et al., 2020; Yockey, 2016). We established a five-point Likert scale for each instrument to standardize the questionnaire package.

The first part included questions related to demographic characteristics such as age, gender, and nationality. The second part of the questionnaire included self-regulation, smartphone use, and procrastination questions. A single item was used to measure academic performance. Students who participated in the study provided their cumulative GPAs. The question was configured as an open response format (Paul et al., 2012). The supplementary question has been added to capture information about the actual cumulative GPA as follows: “*What is your current cumulative grade point average - GPA?*”. Additionally, we asked participants to estimate their daily smartphone use from 0 hour to 24 hours (i.e., ratio variable) and if they considered themselves as addicted or not addicted (i.e., dummy variable).

Self-regulation. The scale has been first operationalized in Germany by Schwarzer, Diehl and Schmitz (1999). This 10-item scale measures an individual goal-pursuit propensity and the difficulties associated with it. To achieve such purpose, individuals must focus on attention on the task (e.g., learning in an online class setting) and keep a favorable emotional balance (e.g.,

transition to the online class setting). Both German (Schwarzer et al., 1999) and English (Diehl et al., 2006) versions presented high internal consistency, Cronbach's α were respectively .76 and .80. Item example is #1 "*I can concentrate on one activity for a long time, if necessary.*" In our sample, Cronbach's α was .82. Interitem correlations were comprised between .03 (between #item 5 and #item 8) and .73 (between #item 3 and #item 4). The 10 items had a moderate to highly satisfactory inter-item correlations as suggested by Cohen and Swerdlik (2005).

Smartphone addiction. We assessed smartphone use using the 10 items of the smartphone addiction short scale developed by Kwon, Kim, Cho, and Yang (2013). In their South Korean sample, researchers have obtained an overall Cronbach's α of .91, thus confirming its internal validity. For example, item #3 is "*Feeling pain in the wrists or at the back of the neck while using a smartphone.*" In the present study, Cronbach's α was .87. Interitem correlations were comprised between .04 (between #item 1 and #item3) and .65 (between #item2 and #item3). The 10 items had a moderate to highly satisfactory inter-item correlations as suggested by Cohen and Swerdlik (2005). While psychometric properties of the original scale have been investigated among adolescents (Kwon et al., 2013), validity and reliability of the smartphone addiction scale have been assessed using a university sample in Turkey (Demirci et al., 2014), as well as in Malaysia (Ching et al., 2015). Validity and reliability of the shortened version of the smartphone addiction scale have been assessed using a university sample in Belgium and Spain (Lopez-Fernandez, 2017).

Procrastination. To evaluate students' procrastination, we used the 5-item questionnaire first developed by McCloskey (2011), who obtained an internal consistency of .93. The following instruction introduced a series of 5-items: "How much do you, yourself agree to the

following statements?” (McCloskey, 2011, p. 57). Further validation in different samples has been found and has shown strong internal consistencies. Both Yockey (2016) and Brandogarrido et al., (2020) obtained a Cronbach’s α of .87. An item example is #2 “*I know I should work on course work, but I just don’t do it.*” In the present study, Cronbach’s α was .91. Inter-item correlations were comprised between .69 (between #item 1 and #item2) and .95 (between #item3 and #item4). Given the theoretical background of the scale, the five items had a satisfactory inter-item correlations as suggested by Cohen and Swerdlik (2005).

To ensure the readability and the overall quality of the present questionnaire, a team composed of one undergraduate student and one faculty member evaluated the questionnaire package with the help of a rating grid, including wording quality, items pertinency, and clarity of instruction (Fowler, 2013). The questionnaire was modified accordingly before sending it out to students. It has to be noted that none of the items has been deleted or significantly modified.

3.4. Descriptive statistics and mean comparisons

The sample was composed of 113 (47.5%) male participants and 125 (52.5%) female participants. We asked participants to indicate their nationality, and they described themselves as Emiratis (n = 233; 97.9%). The sample was also composed of other Middle Eastern students (n = 4; 1.7%) and one American (i.e., 0.4%). Most of the respondents completed a bachelor’s degree (n = 146; 61.3%); the number of master’s degree students among the respondents was 91 (38.2%). The mean age of the students was 23.55. The cumulative GPA was obtained through an open question, and the data showed an average of 3.28. Finally, in our sample, students indicated spending an average of 7.20 hours per day on their smartphones and slightly more than the majority considered themselves non-addicted (n = 128; 53.8%) against addicted (n = 110;

46.2%). We conducted a sensitivity power analysis using G*Power version 3.1.9.6 (Faul et al., 2007). For the given sample size $N = 238$ at a significant criterion of $\alpha = .05$ and achieving a power of 0.95, we detected a medium effect size of $\rho = 0.21$ (Cohen, 1992).

Not surprisingly, our data do not follow a normal distribution. The Shapiro-Wilk test indicated significant results for our data ($p < .001$). A recent meta-analysis showed that research in health, education, and social science uses, for a large majority, non-normal data distribution (Bono, Blanca, Arnau, and Gomez-Benito, 2017). In addition, kurtosis and skewness indicators were not satisfactory; data is deemed “normal” if the skewness is between -2 and +2 and the kurtosis is between -7 and +7 (Hair et al., 2010; Byrne, 2010).

A first analysis of mean comparison through the Kruskal-Wallis H test indicated significant differences. There was a statistically significant difference between number of hours spent on smartphone ($H(1) = 28.677$, $p < .001$) indicating that students who perceived themselves as addicted are spending more hours per day on their smartphone ($M = 8.5$, $SD = .34$) than students who perceived themselves as non-addicted ($M = 6.07$, $SD = .23$). In the same vein, we found significant differences on self-regulation scores ($H(1) = 13.701$, $p < .001$), smartphone addiction ($H(1) = 29.458$, $p < .001$), and procrastination ($H(1) = 6.616$, $p = .010$), but no significance was found for GPA scores ($H(1) = 1.473$, $p = .225$).

The same pattern has been found when running the one-way ANOVA analysis, a parametrical test that, in some situations showed robustness toward non-normal data distribution (Box and Watson, 1962; Lanz, 2013; Blanca, Alarcón, Arnau, Bono, and Bendayan, 2017). Significant differences have been found between students who perceived themselves as addicted and students who perceived themselves as non-addicted on self-regulation scores ($F = 15.762$, p

< .001, $\eta^2 = .06$), procrastination ($F = 5.910$, $p = .016$, $\eta^2 = .03$), and on the total hours spent per day on a smartphone ($F = 37.245$, $p < .001$, $\eta^2 = .14$), but no significance was found for GPA scores ($F = 1.083$, $p = ns$, $\eta^2 = ns$).

3.5. Analytical strategy

A few strategies can be followed to achieve a normal distribution when the data is not normally distributed, such as removing and handling outliers. However, we believe that outliers are very informative in our case and are considered a normal part of the process in our specific field of study.

Mean comparisons have been conducted using the Kruskal-Wallis H test because our data violated the assumptions of the ANOVA test and specifically related to the normal distribution assumption. One of the advantages of the Kruskal-Wallis test is that variations within groups are established based on the relationship between the sample size for each group in contrast to a simple combined variance estimate, thus tackling the heteroscedasticity issue (Lantz, 2013). The Kruskal-Wallis H test determines whether the medians vary between two groups or more (Lantz, 2013).

The same applies to correlation analysis where most scholars employ Pearson's correlation in their studies. In the context of non-normal distribution, Newson (2002) recommends using Kendall's Tau (i.e., Kendall's τ_a) over Pearson's and Spearman's approaches. Indeed, scholars identified that "confidence intervals for Spearman's r_s are less reliable and interpretable than for Kendall's τ -parameters" (Kendall and Gibson, 1990, p. 47). A recent confirmation has been found in Croux and Dehon (2010, p. 12), where authors indicated that "the Kendall correlation measure is more robust and slightly more efficient than Spearman's rank correlation, making it the preferable estimator."

Therefore, we decided to select another strategy that orients the analysis toward specific statistical approaches, such as non-parametric analysis and the use of partial least square.

Finally, we opted for the Partial Least Square - Structural Equation Modeling (i.e., PLS-SEM) regressions to estimate relationships and predictive characteristics of our model. Our analytical approach is considered the most appropriate for the predictive nature of the study and strong enough to test our ideas based on the minimum sample size recommendations among scholars. For a few researchers, the SEM procedure requires a minimum sample size of $n = 100-150$ (Tinsley and Tinsley, 1987; Anderson and Gerbing, 1988; Ding, Velicer, and Harlow, 1995; Tabachnick and Fidell, 2001); for others, a sample size of $n = 200$ is the minimum (Boomsma and Hoogland, 2001). A more rigorous view of the minimum sample size is proposed by Kline (2022), where the ratio of observation per parameter should be 10:1. We did not find any missing data in our sample, and multicollinearity has been fixed to propose a better model and thus avoid redundancy (Tabachnick and Fidell, 2007). Our sample's statistical attributes led us to retain the PLS method over the common bootstrapping method found in structural equation modelling (SEM). Among these attributes, we have identified the number of constructs and indicators present in our model, the overall objective of the present study (i.e., to clarify the utilization of smartphone within the online learning setting), the relatively small sample size, and the lack of normality in our sample (Hair et al., 2010).

3.5.1. A PLS-SEM approach

A visual specification of our model and hypothesis is provided (see figure 1). They represent the expected relationships among our endogenous variables (i.e., Procrastination, Smartphone addiction, and GPA) and exogenous variable (i.e., self-regulation). The model has been established on the idea that self-regulation is theoretically a variable that foster academic

activities and outcomes. Within our model, self-regulation does not depend on another variable. This is in contrast to GPA that is influenced by several other indicators as identified in the literature review.

In order to proceed with the identification of our model we made sure that the data collection would result in a fruitful analysis. Therefore, we specified the use of PLS-SEM and made sure that required thresholds have been followed such as minimum sample size. PLS-SEM demonstrates an excellent performance in analyzing small sample sizes along with non-normal distribution - in other words PLS-SEM approach is a robust method to deviations from normality (Kock, 2016). SmartPLS software offers a wide range of model-fit measures and respectively SRMR, NFI (i.e., Normed Fit Index), χ^2 . The Standardized Root Mean Square Residual (i.e., SRMR) assesses the average discrepancy between observed and expected correlations. A good fit is established when SRMR is less than .08 (Hu and Bentler, 1999). The Normed Fit Index (i.e., NFI) compares real χ^2 value with a supposed χ^2 value. The closer the NFI to 1, the better is the fit (Lohmöller, 1989). Other fit indices are GFI (Goodness of Fit Index), PGFI (Parsimony Goodness of Fit) and CFI (Comparative Fit Index). They are deemed acceptable when they are > .8 and excellent when > .9 (Baumgartner and Homburg, 1995; Doll, Xia, and Torkzadeh, 1994). Other scholars such as Mulaik et al. (1989) indicated that indices such as PGFI are not concerned with a threshold and are more useful for model comparison.

Outer loadings, outer weights, standard errors, Joreskog rho, average variance extracted (i.e., VE) composite reliability (i.e., CR), and VIF have also been assessed to attest the overall scales' robustness. Results as shown in Table 1 indicate that the scales show both robustness and a good fit to the data. Factor loading with value less than 0.6 have been deleted (Hair et al., 2010) which

was the case for three items for self-regulation and one item for smartphone addiction (see appendix).

Insert Table 1 about here

4. Results

4.1. Descriptive and correlation analysis

We first checked if a gender difference existed in the perceived smartphone use. A between-subject analysis indicated non-significant mean differences between men and women on their propensity to spend more or less time on their smartphones. Descriptive statistics are displayed in Table 1 along with correlation's coefficients (i.e., Kendall's tau: r_τ).

Insert Table 2 about here

As for results, younger students were more likely to have scores that ranked higher on estimated hours spent on smartphone per day ($r_\tau = -.138$, $p < .001$), as well as scores that ranked lower on self-regulation ($r_\tau = .094$, $p < .001$). Those with lower GPA were more likely to have scores that ranked higher on estimated hours spent on smartphone per day ($r_\tau = -.147$, $p < .001$), have scores that ranked higher on procrastination ($r_\tau = -.137$, $p < .001$), and lower on self-regulation ($r_\tau = .167$, $p < .001$). Students with higher self-regulation scores were more likely to have scores that ranked lower on smartphone addiction ($r_\tau = -.250$, $p < .001$), and lower on procrastination ($r_\tau = -.156$, $p < .001$), and higher on GPA ($r_\tau = .167$, $p < .001$). Students with

higher procrastination level were more likely to have scores that ranked higher on smartphone addiction ($r_{\tau} = .372, p < .001$).

4.2. Model's estimates

Estimation and reporting of results are the last step in PLS-SEM analysis (Kline, 2022). Using Smart-PLS to estimate goodness-of-fit, we obtained acceptable to very good fit to the data (Hair et al., 2017). Our model depicted in figure 2 obtained the following criteria (refer to path coefficients in parentheses in figure 2): $X^2 = 680.380$, SRMR = .076, NFI = .772; GFI = .807; PGFI = .650; CFI = .831).

Nonetheless, PLS-SEM is also limited as it does not provide a global scalar function. As such, the global goodness of fit (i.e., GoF) does not match the overall PLS-SEM objective. Henseler and Sarstedt (2013) have confirmed that GoF is not a fit measure as indicated by Tenenhaus et al. (2004) rather a useful indicator for a PLS multi-group analysis (PLS-MGA). If the PLS-SEM model is compared to multiple other models then GoF calculation and interpretation is justified (see Hair et al., 2022).

Standardized estimates are presented in figure 2. Hypothesis 2 is partially supported: the relationship between self-regulation and smartphone use indicated a significance at the 95% confidence level ($\gamma = -.16$). The same conclusion is adopted for Hypothesis 3: we partially confirmed that self-regulation negatively predicted procrastination ($\gamma = .19$) because of the 95% confidence level. Hypotheses #4, #5, and #6 are significant at the 99% confidence level in the expected direction; thus, we confirmed hypothesis #4, #5, and #6. Respectively, self-regulation predicted GPA ($\gamma = .23$), procrastination negatively predicted GPA ($\gamma = -.26$), and positively predicted smartphone use ($\gamma = .54$).

Hypothesis 1, while being rejected, might be the expression of an interesting relationship among students between the intensive use of their smartphone and their GPA. While we were expecting a negative relationship, we found a positive and significant relationship between smartphone use and GPA ($\gamma = .20$).

5. Discussion

Smartphones are becoming more pervasive in our everyday life, and while they're omnipresent among the young population, elderly people will not be exempt from its penetration (Deloitte, 2018). The COVID-19 pandemic has forced universities to accelerate their transition to an online teaching method, reinforcing the use of online academic procedures. Our results are useful for an online setting educational system regardless of the forces that have led to such learning choices. Both COVID-19 and post-COVID 19 literatures have been presented. While at home or outside the campus, it is obvious that students are using their smartphones, and our sample indicated an average use of 7 hours a day. Precisely, we found a negative relationship between age and time spent utilizing smartphones, where it was found that younger students spent more time on their smartphones. This first result is relatively similar to the one found in van Deursen, van Dijk, and ten Klooster (2015) among a Dutch sample; slightly less than the half of the respondents perceived themselves as being addicted. On the other hand, since gender did not present any significant results, we decided to exclude this variable from subsequent discussions. Therefore, our study offers a different direction in comparison to others conducted in the Middle East region (Özer, Demir, & Ferrari, 2009; Albursan et al., 2022).

5.1. Teaching and fostering self-regulation

The results indicated that self-regulation, which is the ability to adapt oneself to new circumstances, or context (Karoly, 1993), had a negative impact on smartphone use (H2) and procrastination (H3). Results were significant at 95% level of confidence and the direction of the relationships were as expected. Considering these results, when students are regulating themselves by setting goals and embracing changes, there are more likely to be fewer procrastinators (Rahmani and & Mohammadi, 2017) and smartphone addicts (Soror et al., 2012). In this respect, this study makes an important contribution to the body of literature and allows university counselors and educators to propose workshops or webinars on how to self-regulate in an academic online setting. Indeed, the temptation to procrastinate is even stronger in the comfort of students' own homes and self-regulation appears to be a solution in our study. Consequently, setting up a clear work schedule, avoiding task uncertainty, and planning for interruptions can be considered as solutions to tackle procrastination temptation and foster academic productivity (Nota, Soresi, and Zimmerman, 2004). There is an essential benefit of self-regulation in our study. Hypothesis 4 stipulated that self-regulation was positively related to academic performance (i.e., GPA). Specifically, engaging in the effort of regulating oneself was associated with academic performance (Richardson et al., 2012), and we found similar results in our sample of university students. We enhance the body of literature in this area by providing evidence that self-regulation is also a predictor of academic performance in a new environmental context such as the online academic setting. We therefore offered an extension of the contextual characteristics established by Pintrich (2004) by signifying that the online academic setting might be one of them. In the same vein, we aimed to close the loop by exploring the impact of procrastination on GPA (H5) and smartphone use (H6). In our sample, procrastination negatively led to lower GPA compared to students who procrastinate less; our results are siding with recent

literature on this topic (Gustavson & Miyake, 2017; Kertechian, 2018). In the same vein, the more a student procrastinates, the more he or she will spend time on his or her smartphone and then become addicted to it (Geng et al., 2018). In addition, the mediating role of procrastination has been established in a study where Instagram addiction predicted academic results in the presence of procrastination only (Pekpazar et al., 2021).

Overall, our findings indicate that self-regulation is a good factor to foster academic outcomes and reduce procrastination and smartphone excessive use.

5.2. Addicted to a smartphone but addicted to higher GPAs

Counterintuitive results have been found when analyzing the association between smartphone use and GPA. While studies identified certain findings (e.g., Amez and Baert, 2020) relating to the negative relationship between smartphone use and GPA (Lepp et al. 2015; Hawi and Samaha, 2017; Chen and Yen, 2016; Junco and Cotton, 2012; Levine et al., 2012; Karpinski et al., 2013; Rosen et al., 2013), we found a strong and positive relationship between excessive smartphone use on GPA scores. In other words, the more the student spends times on his or her smartphone, the higher his or her GPA score is. The academic online setting imposed by the COVID-19 regulations might have impacted students to intensively use their smartphone for educational and academic purposes. Students may engage in group activities or share their knowledge on a specific assignment with other students, more easily with the help of a smartphone in the current environment. This result matches a recent study identified in the literature that also provides a basic rationale about this positive relationship; students who have an extensive usage of their smartphone toward more study-related use would obtain higher academic results than those using their phone for non-study-related activities (Abbasi et al., 2021). This result goes against other studies done during the COVID-19 pandemic that have found a negative relationship between

the excessive use of smartphones and academic results (Albursan et al., 2022; Sunday; Adesope, & Maarhuis, 2021) and specifically in the Middle-East (Alotaibi et al., 2022). In the UAE context, universities remained closed, but coffee shops, restaurants, malls and other gathering places remained opened during the pandemic and students had the possibility to meet group members or other students in these places. Nevertheless, the smartphone use path to GPA indicated an important magnitude, thus confirming its unambiguous positive effect in our sample. A single study has found similar results indicating that study-related excessive use of smartphones would have a positive impact on academic performance (Abassi et al., 2021). To the best of our knowledge, we did not find other studies indicating that smartphone use strongly predicts a higher level of GPA. In light of this intriguing result, we provide an added value to current knowledge and encourage scholars to engage in this direction. Therefore, qualitative studies might explore the motivation behind the use of smartphones in this unique academic context. Our study did not support previous studies indicating that smartphone use was negatively related to academic performance (Albursan et al., 2022; Alotaibi et al., 2022) and we proposed a renewed approach concerning smartphone use and its impact on academic performance.

In an online academic setting, it seems that excessive use goes hand-in-hand with academic results. Additionally, it appears that self-regulation is an important factor on how students can use their smartphone excessively but positively. The mean for self-regulation in our sample was higher than the mean of excessive smartphone. Therefore, students can engage in controlling their behavior or emotions to foster their academic performance. Thus, if the intensive use of smartphones is governed and organized through educational goals, then students can benefit from this excessive use for more positive academic outcomes (Abbasi et al., 2021). Therefore,

this type of orientation takes the opposing view of a deteriorated learning process through the extensive use of smartphones (Sunday, Adesope, & Maarhuis, 2021). To go further, we explained earlier that self-regulation was an essential characteristic among students to enable educational productivity, thus, we propose that excessive smartphone use went through a conceptual shift and became a positive psychological state for students with a higher level of self-regulation. This latest contribution offers a new theoretical perspective for the association between smartphone excessive use and academic performance through the presence of self-regulation. Our literature review provided some indications about this shift because of the positive relationship between self-regulation and academic achievement (e.g., Estévez et al., 2021; Iqbal et al., 2021). Therefore, excessive usage of smartphones is possibly positive if students are engaged in study-related utilizations of their device and demonstrate strong regulation of their learning process.

Overall, our study suggests that a smartphone might be considered an educative tool for university students while establishing self-regulation procedures to avoid being in a situation where smartphone use would have a negative impact on academic performance exclusively.

6. Limitations and recommendations

Our study is not without limitations. The sample size was relatively small regarding the academic population either in UAE or around the world. Consequently, our results could not be generalized to other cultural contexts or different populations of students. In addition, the results would have been more reliable if the sample size was larger. That being said, we reached the minimum sample size recommended by scholars in the case of SEM analysis. One additional limit of the present model are the fit indices. While the majority of them are considered

acceptable to excellent, the Parsimony Goodness of Fit Index (PGFI) was equal to .650 which is considered as a relatively weak value, but one can consider that this indices is not really relevant within our framework (Mulaik et al., 1989).

Our study has been conducted in the midst of a rapid change towards an online environment. While this was an objective of the present study (i.e., academic performance in an online academic setting), results have been undoubtedly affected. Therefore, results must be compared either with on-campus settings or with other studies including online academic settings, to verify the relationship between smartphone use and academic performance.

More generally, this study used self-reported measures to test our hypothesis, while other research on smartphone addiction used more direct approaches in measurement such as mobile applications (Lin et al., 2015).

We could not distinguish whether the positive impact of smartphone excessive use was explained by the impact of the pandemic or whether students were really engaged in a positive cycle where smartphones are considered devices to help them achieve better grades. Questions on the specific use of smartphones need to be explored and finding solutions in future studies to identify types of activities that students are engaging when using their smartphone would be crucial.

Finally, there are many ways to improve the present model, such as including moderators with the help of individual differences, since the literature shows that personality affects academic performance (Kertechian, 2018).

Appendix

Self-Regulation Questionnaire - Schwarzer, Diehl, Gerdamari, and Schmitz, 1999
<ol style="list-style-type: none">1. I can concentrate on one activity for a long time, if necessary.2. If I am distracted from an activity, I don't have any problem coming back to the topic quickly.3. If an activity arouses my feelings too much, I can calm myself down so that I can continue with the activity soon.4. If an activity requires a problem-oriented attitude, I can control my feelings.5. It is difficult for me to suppress thoughts that interfere with what I need to do.6. I can control my thoughts from distracting me from the task at hand.7. When I worry about something, I cannot concentrate on an activity.8. After an interruption, I don't have any problem resuming my concentrated style of working.9. I have a whole bunch of thoughts and feelings that interfere with my ability to work in a focused way.10. I stay focused on my goal and don't allow anything to distract me from my plan of action.
Smartphone Addiction Scale Short Version - Kwon, Kim and Young (2013)
<ol style="list-style-type: none">1. Missing planned work due to smartphone use2. Having a hard time concentrating in online class, while doing assignments, or while working due to smartphone use.3. Feeling pain in the wrists or at the back of the neck while using a smartphone.4. Will not be able to stand not having a smartphone.5. Feeling impatient and fretful when I am not holding my smartphone.6. Having my smartphone in my mind even when I am not using it.7. I will never give up using my smartphone even when my daily life is already greatly affected by it.8. Constantly checking my smartphone so as not to miss conversations between other people on Twitter or Facebook.9. Using my smartphone longer than I had intended.10. The people around me tell me that I use my smartphone too much.
Procrastination questionnaire Short Version - McCloskey (2011)
<ol style="list-style-type: none">1. I put off projects until the last minute.2. I know I should work on assignment/course work, but I just don't do it.3. I get distracted by other, more fun, things when I am supposed to work on assignment/course work.4. When given an assignment/course work, I usually put it away and forget about it until it is due.5. I frequently find myself putting important deadlines off.

Nb: Items in bold have not been retained in the analysis

Table 1. Construct and discriminant validity (i.e., Factor's loading, Joreskog's rho, AVE, CR, VIF and HTMT)

Scales <i>Items</i>	Outer Loadings	Outer Weights	Standard Errors	Joreskog's rho	Average Variance Extracted	Composite Reliability	VIF
Self-regulation							
<i>Item1</i>	.64	.18	.07	.83	.50	.87	1.401
<i>Item2</i>	.74	.23	.06				1.808
<i>Item3</i>	.71	.17	.06				1.827
<i>Item4</i>	.67	.21	.06				1.625
<i>Item5</i>	.74	.22	.06				1.644
<i>Item6</i>	.72	.18	.05				1.635
<i>Item7</i>	.69	.18	.05				1.438
Smartphone addiction							
				.89	.51	.90	
<i>Item1</i>	.72	.20	.09				1.891
<i>Item2</i>	.76	.22	.09				2.149
<i>Item3</i>	.63	.10	.12				1.571
<i>Item4</i>	.57	.10	.11				1.550
<i>Item5</i>	.72	.12	.09				2.198
<i>Item6</i>	.75	.16	.07				2.225
<i>Item7</i>	.67	.15	.07				1.575
<i>Item8</i>	.76	.17	.08				1.869
<i>Item9</i>	.77	.15	.07				2.006
Procrastination							
<i>Item1</i>	.83	.22	.07	.91	.73	.93	2.242
<i>Item2</i>	.89	.22	.05				3.008
<i>Item3</i>	.84	.25	.07				2.187
<i>Item4</i>	.85	.21	.06				2.586
<i>Item5</i>	.88	.27	.06				2.779
Heterotrait-monotrait ratio (HTMT)							
Procrastination – GPA = .20							
Smartphone Addiction – GPA = .11							
Smartphone Addiction – Procrastination = .60							
Self-regulation – GPA = .25							
Self-regulation – Procrastination = .22							
Self-regulation – Smartphone Addiction = .30							

Note: 1) Standard error for self-regulation is .07; standard error for procrastination is .14; standard error for smartphone addiction is .09. 2) three items from self-regulation and one item

from smartphone addiction have been removed from the final model because of a not reaching factor loading thresholds (Hair et al., 2010).

Table 2. Correlation analysis (r_t) and descriptive statistics

Variables	Mean (SD)	1	2	3	4	5
Age (1)	23.55 (3.95)					
GPA (2)	3.28 (.44)	.060				
Hours per day (3)	7.20 (3.27)	-.138	-.147			
Self-regulation (4)	3.70 (.71)	.094	.167	-.091		
Smartphone addiction (5)	2.87 (.92)	-.016	-.008	.051	-.250	
Procrastination (6)	2.74 (1.11)	.016	-.137	.067	-.156	.372

Nb: Items in bold denote a significant at .01 level; r_t = Kendall's Tau; **GPA**= Grade Point Average; **Hours per Day**= Number of hours spent on smartphone in a day

Figure 1. Model specification

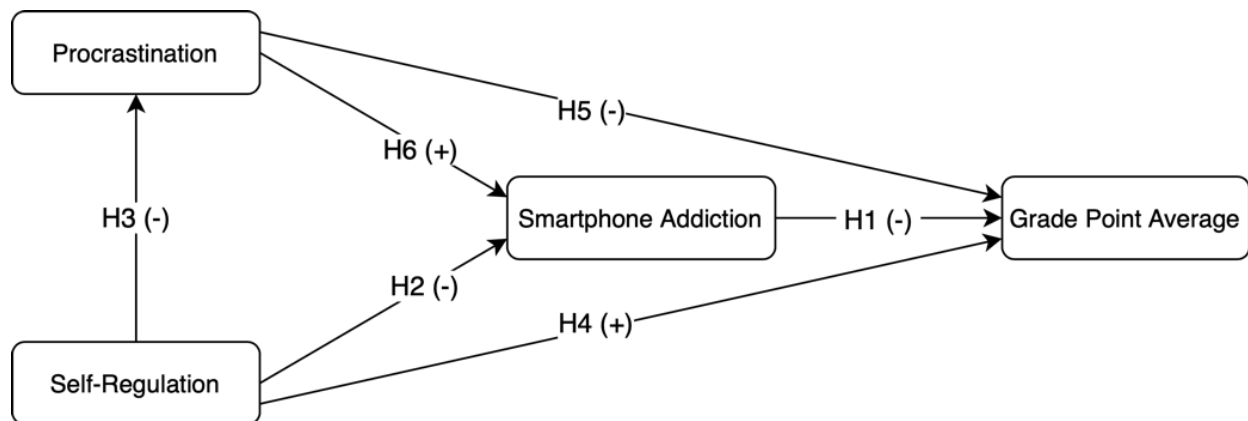
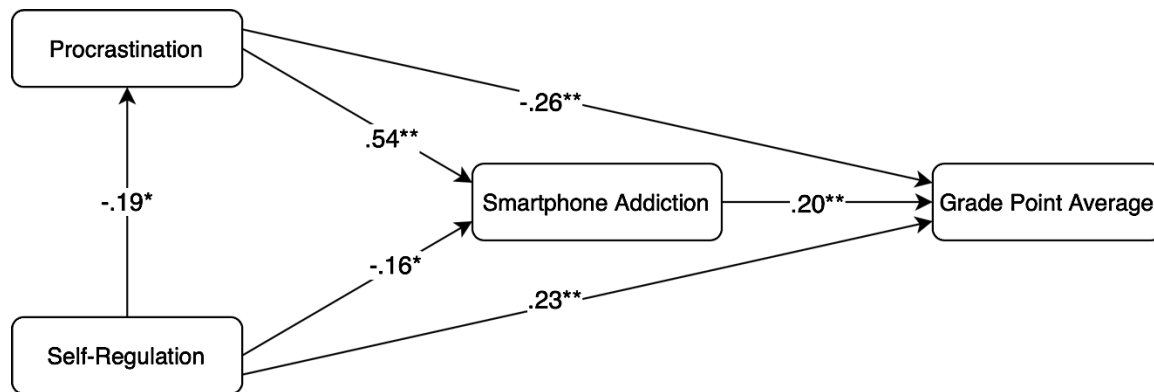


Figure 2. Path analysis



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