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The relationship between smartphone use and students` academic performance

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ABSTRACT

This study was designed to measure the impact of smartphone usage among college students on their current academic success. We report the results from a survey among 99 undergraduate student iPhone users in a large Midwestern U.S. university. The survey combines objective smartphone use time directly obtained from Apple's ScreenTime feature with official GPA and ACT/SAT scores from university records. We evaluate how GPA and self-reported measures of academic success are determined by ACT/SAT scores, demographics, school-related variables, study-related variables, socio-economic variables and time spent using one's smartphone. Our results suggest that one additional hour of phone use per day lowered current term GPA by 0.152 points on average. Time spent using a smartphone significantly reduces GPA and self-reported measures of academic productivity.

1. Introduction

Smartphones have become an integral part of university students' lives as they use them throughout the day for reasons such as communication, productivity, entertainment, utilities, social networking, and gaming (Kwon et al., 2013). Widespread smartphone ownership among university students triggered an interest in investigating the impact of smartphone use in all aspects of university students' lives, particularly academic performance (Karpinski et al., 2013). Technology certainly supports better learning opportunities such as internet resources and availability of mobile computers; however, excessive or problematic smartphone use can have negative impacts on study-related activities. This concept is defined as "excessive use of smartphones that interferes with the daily lives of the users" (Elhai, Levine, Alghraibeh, et al., 2018; Elhai, Levine, O'Brien, & Armour, 2018; Lee et al., 2015; Turel & Serenko, 2012). Understanding the impact of smartphone use on academic performance is an important research issue to address. Smartphone overuse can impair academic functioning, when students use their phones in class instead of paying attention, and play on their phones in the evenings instead of studying and doing homework. For example, frequent interruptions due to excessive smartphone use could be associated with performance loss (Duke & Montag, 2017).

A substantial body of work has studied the correlation between smartphone use and academic success. However, most research measured smartphone use with self-report surveys rather than objective phone logs. However, such self-reported measures can be subjective and biased, especially in problematic use cases (for instance via experienced time distortions on the smartphone; see Lin, Lin, et al., 2015; Montag et al., 2015). Furthermore, it is possible to observe significant differences between self-reported estimation of smartphone use frequency and objective use (Ryding & Kuss, 2020). Therefore, less is known about relations with objectively-measured smartphone usage. The purpose of this study is to measure the association between smartphone use and academic performance after adjusting for potential individual differences and background factors. In this study, we used a survey of public university students in Ohio (USA) conducted in Fall 2019 that contains demographic, socio-economic, and other characteristics of the students. We then combined these data with students' actual GPA, ACT/SAT scores obtained from their academic transcripts and with data obtained by asking these students to provide screenshots from their smartphones

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with actual ScreenTime measures. We empirically examine how students' college GPA is affected by smartphone usage time and other relevant variables.

Objective phone use was obtained with the iPhone's ScreenTime feature, assessing use minutes, number of pickups and notifications. In this regard, our paper is one of the first in the literature that utilizes ScreenTime applications to assess the impact of smartphone usage on students' current academic success using multiple regression analysis. We also contrast our main results with the estimates obtained by using self-reported frequency of smartphone use.

Indeed, there are several positive aspects of smartphones especially during the COVID-19 pandemic as many students have been isolated and smartphone use provided them with access to friends, family and support networks and online education. On the other hand, there are several mechanisms that provide possible explanations as to why smartphone overuse may interfere with study-related activities, thus can have a negative impact on academic performance. We draw on two fundamental approaches to conceptualize our empirical analysis. The first one is based on cognition theories and the second one is the study-leisure trade-off hypothesis. First of all, smartphone use can have a negative impact on academic outcomes through cognitive overload, attention deficit, procrastination, surface learning and as a distraction factor in focus to studying. Cognitive theories such as the limited capacity model of mediated message processing (Lang, 2000), capacity sharing theory (Kahneman, 1973; Navon & Gopher, 1979), and the threaded cognition model (Salvucci & Taatgen, 2008) suggest that people have finite cognitive resources in processing information. Incoming information that increases resource demands will result in worse task performance. Therefore, greater smartphone use frequency may interfere with task performance needed to engage in routine study-related activities (Liebherr et al., 2020).

For example, reading/replying to incoming messages on a smartphone may conflict and interfere with studying course materials. Similarly, using a smartphone could result in a flow experience from the pleasurable features of the phone with which the individual is interacting (Csikszentmihalyi, 2013). However, when a student attempts to work on specific tasks (e.g., schoolwork), checking social media on smartphone or going through notifications can disrupt their flow state previously experienced during the task, making the task less enjoyable and more difficult to complete (Montag & Diefenbach, 2018). Smartphone use can distract from studying by providing an alternative and possibly more psychologically rewarding way of occupying one's time, a way which, unlike studying for exams, offers immediate satisfaction (e.g., playing video games, following friends on social networking apps, looking at memes) (Elhai et al., 2019). Even though technology definitely supports student learning in many ways (George & DeCristofaro, 2016; Remón et al., 2017), excessive smartphone use may be a distraction factor in academic achievement.

Finally, a trade-off between preferences for leisure vs. study time is another plausible explanation for a potentially negative association between smartphone use frequency and GPA. Students who put more emphasis on leisure relative to grades or future earnings will spend less time studying and more on leisure activity (for further discussion see Greene & Maggs, 2017). Using the smartphone is one of the most preferred leisure activities of the current generation, whereas earlier generations would have listened to music or spent time socializing in-person with friends (please note that the smartphone also can be used to listen to music or to socialize with others, but not in-person). Students who value leisure might display more frequent smartphone use and this can also result in disruptions in study-related activities and consequently obtain lower grades. Smartphone provides a convenient tool to tradeoff study time to leisure, decreases study time and consequently some students` grades deteriorate.[1]

Taken together, the above theories suggest that smartphone use can act as a distraction from studying, thereby reducing students' academic performance and achievement. Thus, we expect that more time spent on the smartphone, especially on activities that are not related to academics and study, decreases college GPA. In order to examine this empirically, we use a multiple regression analysis and consider several variables that are studied in the empirical literature and select the most important ones that control for individual differences between students. Then we assess the association between smartphone use and academic performance. We anticipate that increased smartphone use is negatively correlated with academic performance.

2. Review of empirical literature

By analyzing self-reported smartphone use intensity among college students at one university, Junco and Cotten (2012) found that spending a fair amount of time on smartphones while studying negatively affects GPA. Similarly, with self-reported usage intensity and productivity variables, Wentworth and Middleton (2014) analyzed a sample of 480 US university students, finding that those with greater technology use spent less time studying, which had a strong negative relationship on GPA. Rosen et al. (2013) used data from US students aged 11 to 25 years, and those who used Facebook and texted while studying had lower GPAs.

An experimental study found that students who used Facebook while attending class lectures obtained lower scores compared with students who did not (Wood et al., 2012). A few other papers also focused on Facebook use (Busalim et al., 2019; Feng et al., 2019; Wakefield & Frawley, 2020); however, in recent years students mostly use their smartphones for other more popular social networking sites besides Facebook and messaging so the focus has shifted to overall smartphone usage intensity. Based on self-reported smartphone use, several studies have found a negative association between smartphone use and academic performance (Hawi & Samaha, 2016; Jacobsen & Forste, 2011; Judd, 2014; Karpinski et al., 2013; Kim et al., 2019; Lepp et al., 2014; Nayak, 2018; Rosen et al., 2013; Runyan et al., 2013; Wentworth & Middleton, 2014). Among university students, those who spent more time using smartphones spent less time studying, which had a strong negative relationship to GPA. In summary, high frequency of smartphone use and messaging was found to be negatively related to college students' GPA in correlational studies. However, all of the previous studies relied on self-reported smartphone usage, with the exception of Giunchiglia et al. (2018) studying 67 students in Italy, and Felisoni and Godoi (2018) with 43 students in Brazil using objective ScreenTime data. Giunchiglia et al. (2018) relied on bivariate correlational analysis only (without covariate adjustment), while Felisoni and Godoi (2018) used the rank of students instead of GPA to measure academic performance.

Several researchers have pointed to multi-tasking as an explanation for the negative relationship identified between smartphone use and academic performance. Those studies noted that smartphone multitasking is responsible for a decline in academic performance (Alghamdi et al., 2020; Choliz, 2010; Jamet et al., 2020; Rice & Hagen, 2010; Uzun & Kilis, 2019; Wammes et al., 2019). College students who show symptoms of excessive mobile phone usage are prone to disruptions in schoolwork and daily activities (Elhai et al., 2019). Consequently, when students use their smartphones excessively, such as messaging and checking social media while studying, these behaviors tend to negatively affect their learning and academic performance. College students also display a form of social dependency on their smartphones. Some students are aware of these negative effects, and appear to be concerned about the interference of smartphone use with school life and social environments; however, most college students think that using mobile phones can strengthen relationships and connectivity with family members and friends (Lepp et al., 2014). College students commonly but erroneously report that multitasking increases productivity (Lin et al.,

[1] We thank anonymous referee for suggesting this possibility.

2015). For the most part, students do not recognize the extent of negative consequences from media multitasking on academic performance, and frequent in-class multi-taskers have lower GPA (Al-Menayes, 2015; Bellur et al., 2015; Clayson & Haley, 2012; Junco, 2012; Lau, 2017).

In a similar line with excessive smartphone use, some researchers focused on gaming, and found that high videogame use was associated with lower GPA (Weaver et al., 2013). Gaming is also of relevance in the present context, because more internet gaming is associated with problematic smartphone use (Leung et al., 2020). Perhaps this is understandable in light of the addictive features built-in Freemium games on the smartphones have in prolonging gaming time (Montag et al., 2019). In addition, some studies that examined in-class test performance found the non-texting participants outperformed those who texted regardless of gender (Ellis et al., 2010; Froese et al., 2010; Leung et al., 2020; McDonald, 2013; Waite et al., 2018). These studies focused on phone use inside of the classroom, and reported that media multitasking was negatively associated with GPA, test performance, information recall, comprehension, and note taking, especially when students multitask to engage in off-task activities.

Previous literature relied on self-reported smartphone use frequency where students identified their usage intensity on a Likert scale. However, such self-reported measures can be subjective and biased, especially in problematic use cases. No study using objective smartphone use data in relation to GPA was done in the U.S. In addition, some studies relied on self-reported GPA. Instead, our analysis is based on actual smartphone screen time data obtained from ScreenTime application and on objective GPA and ACT scores from academic transcripts. We hypothesized that longer overall smartphone usage, as well as longer time spent in some categories of ScreenTime use (Creativity, Entertainment, Games, and Social Networking) would be detrimental for academic outcomes. We also hypothesize that a greater number of smartphone notifications and pick-ups would be detrimental for academic outcomes. We further expect that such a detrimental effect would be in particular due to social media use. We are also interested in assessing the size of this relationship, which may be of interest to policy makers.

3. Method

3.1. Participants

We recruited participants in Fall 2019 from the psychology department's research pool in a large Midwestern U.S. university. Participants located our study on the department's online research portal which promotes department studies, to participate for course research points. Interested participants enrolling were routed to an online informed consent statement, and for those consenting, subsequently routed to an online survey. The study was approved by the university's Social/Behavioral Institutional Review Board.

Among the 181 participants enrolling, 6 participants did not continue past the first few survey questions, and another 6 were duplicates who had already completed the survey, and were excluded. We excluded an additional 5 participants for indicating the same response across many consecutive survey items (more than 30), suggesting insufficient attention. Of the remaining 164 participants,[2] 148 reported currently owning an iPhone (necessary for our design collecting objective smartphone use estimates), and 101 of these participants ultimately provided us with useable screenshots of their smartphone use. After excluding one participant who did not have a current GPA record and restricting age range between 18 and 24 years, our effective sample for analysis included 99 participants.

For further supplemental analysis, we asked for specific categories of ScreenTime; these are creativity, education, entertainment, games, productivity, reading and social networking. We included all available categories without omitting any of them. Social Networking is spending time on any social media. Productivity is calculated by the time the user spends on apps such as Notes, Calculator, office programs and email. Creativity is considered to be the time spent on apps such as Photos. Entertainment includes games and sites including YouTube. However, some students did not send the category screenshots to us, or failed to follow instructions for changing the specific apps and sites to the categories feature in the ScreenTime application, resulting in a sub-sample of 59 participants for analyzing categories of use. Even though our sample involved convenience selection of subjects from the student pool, it is fairly representative of the public university student population in the US, based on sample demographic statistics presented below (Table 1).

3.2. Procedure

We first asked participants for the last four digits of their cell phone number and month of birth, so that we could create a non-meaningful identification number based on these two pieces of information. After completing the online survey measures described below, we asked participants for their university student identification number (matched with their non-meaningful identification number) and permission to use this number to locate their academic record (GPA and ACT scores) from the university's online academic portal available to faculty/administrators. Among iPhone-using participants, we instructed them to locate their use estimates using iOS' ScreenTime feature. We provided detailed instructions for taking screenshots of these estimates, and sending the screenshots using email or text messages to us using a dedicated mobile phone number and email address we used for this project.[3] We also instructed participants to include their non-meaningful identification

Table 1
Summary statistics for the full sample with valid ScreenTime daily use data ($N = 99$).

	Mean	SD	Min	Max
Variable				
Current GPA	2.99	0.85	0.24	4
ACT score	21.96	4.076	14	32
Total credit hours	32.75	27.44	6	133
Hours of daily phone use	5.477	2.18	1.600	13.40
Age	19.07	1.33	18	24
Number of siblings	2.49	1.85	0	13
Categorical variables				
Got important things done at school	0.48			
Satisfied with school achievements	0.53			
Sense of accomplishment from school	0.43			
Male	34%			
White	78%			
Hispanic	8%			
Parental income	0.46			
Attended private school	13%			
ACT score missing	0.07			
Using phone more than usual	0.39			
Democrat	38%			
Republican	34%			
Going out for fun	0.94			
In relationship	49%			
Working full time	48%			
Freshman	54%			
Living on campus	48%			
Receiving financial aid	0.87			
Studying at least 6 h/week	0.21			
Regular study habit	0.40			

[2] There were 13 psychology majors (8%), 32 nursing majors (19%), and the other majors had between 1 and 7 participants.

[3] An example of screenshots from the Screentime app can be found in the supplementary online appendix.

number along with the screenshots, so that we could match their ScreenTime data with their survey and academic data. On average, participants sent their screenshots 0.18 days (SD = 1.91) after web survey completion.

3.3. Variables

3.3.1. Demographic and socio-economics variables

We used eighteen variables which were identified in the literature as important predictors of academic success: age in years, gender (coded 1 if male and 0 otherwise), race (coded 1 if the respondent indicated white race and 0 in all other cases), ethnicity (coded 1 if Hispanic vs. non-Hispanic); parental income (coded 1 if >$80,000 yearly income and 0 otherwise), number of siblings, whether the participant attended private high school (1 if yes, 0 if no), whether the participant reported using their phone more than usual in the previous week (1 if yes, 0 if no), indicators (1 if yes, 0 if no) for participant's preferred political affiliation (Democrat, Republican other), whether participant goes out for fun on a weekly basis (1 if more than once a week and 0 otherwise), whether in a romantic relationship (1 if yes, 0 if no), whether working full time (1 if yes, 0 if no), whether a freshman (1 if yes, 0 if no), whether living on campus (1 if yes, 0 if no), whether receives financial aid (1 if yes, 0 if no), whether studies at least 6 h a week (1 if yes, 0 if no), whether has a habit to study regularly for the exams (1 if yes, 0 if no).

3.3.2. Academic measures

Based on the information collected from the academic transcripts we created four variables: current term college GPA, cumulative college GPA, ACT composite score, total credit hours accumulated.[4,5] Data on ACT or SAT scores were not available for 7 of the 99 participants in the sample. Missing values were replaced with the sample average ACT and an additional variable indicating missing values on ACT score was created.

3.3.3. Academic productivity measures

We created three indicator variables measuring academic productivity based on three self-reported variables. The first variable was set equal to 1 for responses “much” or “very much” to the question “To what extent, did you feel you got done the things at school that were most important to you?” and zero otherwise. The other two indicator variables were based on the questions “How satisfied were you with what you accomplished at school?” and “To what extent did you feel a sense of accomplishment from school?” and were scored similarly to the first item (These items were adapted from the scale validated by Kushlev & Dunn, 2015).

3.3.4. ScreenTime feature

We gathered objective data on smartphone use from the screenshots sent to us by participants using iOS' ScreenTime feature. We included very specific instructions for participants on taking the screenshots and instructed them to select the ScreenTime data only for their individual iPhone, rather than any other iOS devices on their account (e.g., iPad, or another iPhone in their family account if applicable). We provided two sets of slightly different instructions based on whether participants were using iOS 12 or iOS 13 (iOS 13 was released around the beginning of our data collection period, but some participants had not yet updated to iOS 13), resulting in slight differences in ScreenTime user interface. We instructed participants to submit the information based on the past week. Participants were instructed to send four screenshots based on the data available from ScreenTime: a) minutes of use, b) minutes spent in most used categories of use (e.g., social networking, entertainment, productivity, etc.), c) number of screen unlocks or “pickups,” and d) number of notifications received. After taking the screenshots, participants were asked to open the Photos app, with instructions to mail or text message the screenshots to us. Some participants did not follow the instructions correctly (e.g., sending only the current day's data, or only sending one screenshot), so we followed up with them to obtain the correct data.

The ScreenTime feature in iOS 12 displays the last 7 days of screen use, while iOS 13 displays only screen use since the most recent Sunday. Therefore, we converted all variables measuring the length of use into daily averages. Similar ScreenTime metrics from iOS have been analyzed in recent literature in relation to socio-demographic and psychological variables (David et al., 2018; Ellis et al., 2019; Gower & Moreno, 2018). We also asked students in the online survey if they were using their phone more than usual in the last week with Likert-type responses from 1 to 5 and we included this variable as a control in the regression.

3.4. Empirical models

For our main sample ($N = 99$), we estimated the following model:

$$Y_i = \beta_0 + \beta_1 Hours\ of\ daily\ phone\ use_i + \beta_2 X_i + \varepsilon_i \quad (1)$$

where Y_i is the participant's current term GPA or one of the three self-reported measures of academic productivity, *Hours of daily phone use*$_i$ is the daily average hours of smartphone use, and X_i is the set of demographic and socio-economics variables (see Section 3.3) used as statistical controls and ε_i is the error term of the model.[6] The model for GPA was estimated using a censored (tobit) regression with left censoring at zero and right censoring at 4. The models for the three binary variables measuring self-reported academic productivity were estimated using probit regression.

For the respondents who had valid data on the categories of ScreenTime use ($n = 59$), we did not estimate a regression model given the small sample size but instead, we presented pairwise correlations of GPA and productivity measures with ScreenTime categories (the respondent's time spent in each of the ScreenTime categories), Pickups (the number of average daily phone pickups), and notifications (the number of average daily notifications received).

3.5. Analysis

We used R software v. 3.63 (R Core Team, 2020) to process and clean our data, using the *careless* package to screen for insufficiently effortful responding (discussed above). We used STATA 15 (StataCorp, 2017) to perform statistical analysis.

4. Results

4.1. Descriptive statistics

Table 1 contains descriptive statistics for the variables used in the regression for the main sample (N = 99) with smartphone use data measured in terms of daily hours of use. The average age in the sample was 19 years and 34% of the participants were males. On average, participants spent 5.5 h (SD = 2.18) per day using their iPhone and had a GPA of 2.99 (SD = 0.85).

The descriptive statistics for the sub-sample ($n = 59$) of the main sample for participants with valid data on ScreenTime categories were

[4] Approximately half of the participants were freshman, for whom current GPA and cumulative GPA were the same.

[5] For 26 out of 164 participants SAT scores were reported on their transcript. These SAT scores were transformed into the corresponding ACT scores using the methodology described in Guide to the 2018 ACT®/SAT® Concordance (2018).

[6] We also estimated all models using cumulative GPA instead of the current GPA and obtained similar results.

similar to the respondents in the main sample in terms of the observable characteristics; they had on average slightly more hours of daily phone use (mean = 5.54, SD = 2.22), as well as slightly lower GPA (mean = 2.89, SD = 0.83) and slightly lower percentage of respondents who reported getting important things done at school, being satisfied with school achievements and having a high sense of accomplishment from school. On average, the participants in this sub-sample spent 2.5 h per day on social networking, 0.79 h on entertainment, 0.55 h on creativity, 0.23 h on creativity, 0.23 h on reading and referencing, 0.17 h on games, 0.12 h on education, and 0.152 on other ScreenTime features. They also had on average 123 phone pickups and received 174 notifications per day. We performed a *t*-test to compare means of the descriptive statistics in the subsample (n = 59 participants) to the remaining 40 participants in the main sample (for all matching variables). The difference in means generated *p*-values ranging from 0.0126 to 0.9104 which indicates no statistically significant differences in the mean of variables between two groups at the 5% level of significance. For this reason and to save space, we did not present a descriptive statistics table for the subsample.

The correlation tables for the full sample and the subsample metrics can be found in the appendix.

4.2. Regression models

Table 2 presents results of estimating regression Eq. (1) for the main sample. There are many individual differences between students, which play a role in determining student grades. Several individual, family and school-related variables were identified in the literature as potential determinants of academic success. Previous literature suggests that the best predictive variables of student achievement include ACT/SAT scores, high school GPA, study habits as well as some demographic and socio-economic factors (Hong, 1984; Duncan & Dick, 2000; Burton & Ramist, 2001; Noble & Sawyer, 2002; Geiser & Studley, 2002; McNabb et al., 2002; Cohn et al., 2004; Cohn et al., 2004; Reason, 2009; Stater, 2009; Grebennikov & Skaines, 2009; Mattern et al., 2010; Danilowicz-Gösele et al., 2017). We investigated whether hours of daily phone use had a separate and measurable impact on GPA and it is the main explanatory variable of interest of our study.

We followed a parsimonious approach to increase the degrees of freedom, and used covariates by only selecting the variables whose bivariate correlations (Appendix A) with GPA were significant at the 1% level (These are hours of daily phone use, race and ACT score). We used these three covariates to run the regression models (Table 2). We also conducted a power analysis for the regression models in Table 2 and

Table 2
Regressions of current college GPA and productivity on daily hours of phone use.

	GPA	Productivity 1	Productivity 2	Productivity 3
Hours of daily phone use	−0.152***	−0.10**	−0.059**	−0.123***
	(0.028)	(0.044)	(0.030)	(0.033)
White	0.228	−0.55	−0.031	−0.006
	(0.181)	(0.14)	(0.14)	(0.14)
ACT score	0.107***	0.031**	0.020	0.001
	(0.015)	(0.015)	(0.014)	(0.014)
Observations	99	99	99	99
Log-likelihood	−97.455	−58.761	−64.225	−58.107

Note. Robust standard errors in parentheses. Column 1 is estimated using Tobit regression. Columns 2, 3 and 4 are estimated using probit regression and the coefficients represent marginal effects on the probability of the outcome. Productivity 1 = 1 if "To what extent, did you feel you got done the things at school that were most important to you?" = 5 or 6, Productivity 1 = 0 otherwise. Productivity 2 = 1 if "How satisfied were you with what you accomplished at school?" = 5 or 6, Productivity 2 = 0 otherwise. Productivity 3 = 1 if "To what extent did you feel a sense of accomplishment from school?" = 5 or 6, Productivity 3 = 0 otherwise.

** $p < 0.05$.

*** $p < 0.01$.

they showed sufficient power to detect estimated effects on the main explanatory variable(s) at the 5% significance level.

According to the first column in Table 2, the coefficient of hours of daily phone use suggests that one additional hour of phone use per day lowered current term GPA by 0.152 points. We also estimated this model with a log-log specification to find elasticities. The results indicate that a 1% increase in smartphone use decreased GPA by 0.33% on average. As expected, ACT scores showed a statistically significant positive effect on GPA.

We should note that when we include other potential covariates from Table 1 into the regression analysis such as other basic demographic controls (age, gender, ethnicity), family background and high school characteristics (parental income, number of siblings, whether attended private school), individual socio-economics controls (political affiliation, indicators for going out for fun, being in relationship and for working full time) and college- and study-related controls, the magnitude of the hours of daily phone use variable was robust and stayed in the range between −0.129 and −0.163. The coefficient on hours of daily phone use was always statistically significant at the 1% level and did not change between hierarchical models containing other sets of control variables. However, to save the degrees of freedom and have a parsimonious approach, we only present results with significant variables and the power analysis shows a sufficient statistical power of over 99% with the estimations in Table 2.

The adjusted R-squared of the first column in Table 2 is 0.45 which suggests that the independent variables explain 45% variation in the dependent variable. We did the following post-estimation analysis for the first column in Table 2. We performed Breusch-Pagan/Cook-Weisberg test for heteroskedasticity. The Chi^2-value of the test is 0.0004 which implies that the null hypothesis of constant variance should be rejected. There is statistical evidence that the variance is not homogenous so we used heteroskedasticity-consistent robust standard errors. Next, we performed normality tests on the residuals. We performed Skewness/Kurtosis tests for Normality and Shapiro-Wilk W test for normal data. Prob>Chi^2-value is 0.068 for Skewness/Kurtosis tests and Prob>z value is 0.0615 for Shapiro-Wilk W test. Both tests indicate the acceptance of normality of residuals. Finally, we used the variance inflation factor (VIF) analysis to check for multicollinearity. VIFs were below 2 for all independent variables suggesting that multicollinearity is not a concern in our estimations.

Table 2 also presents three alternative specifications of Eq. (1) in the second, third and fourth columns, where the dependent variables were the three self-reported schooling productivity measures. These models were estimated using probit regression and the reported coefficients represent marginal effects on the probability of each outcome. The coefficients on daily phone use suggest that an additional 1 h of daily phone use decreased the probability of getting important things done at school by 10 percentage points, decreased the probability of being satisfied with school achievements by 5.9 percentage points and decreased the probability of having a sense of accomplishment from school by 12.3 percentage points. Once again, the power analysis showed sufficient statistical power. The adjusted R-squared is around 0.46 for the models in the last three columns in Table 2. We used heteroskedasticity-consistent robust standard errors; residuals passed the normality test and multicollinearity was not detected.

We performed two other robustness checks that we briefly discuss here. The first exercise was based on the question "I have been using my phone more than usual in the last week". As we explained before, participants sent us their smartphone use in the last 7 days and we took the daily average. However, some participants might have been using their phones more than usual for several reasons during the time they sent us their screenshots. In order to control for this, we separated our main sample into two groups, the first group consisted of strongly agree and agree responses (participants who said they were using more than usual) and the second group consisted of the remaining categories (who said they were either not using more than usual or less than usual). There were 39 students in the first group and 60 students in the second group. After we estimated Eq. (1) for GPA separately for these two sub-groups, the coefficients of daily use in the first group and the second group were very close to each other and to the coefficient in the full sample. The inclusion of this variable did not change the association with GPA. The second exercise used cumulative GPA instead of current GPA. As we indicated before, half of the students in our sample were first semester students; this means that their current and cumulative GPAs are the same. In order to see if this made a difference on our results, we ran the model in first column in Table 2 with cumulative GPA instead of current GPA and we found that the use of current or cumulative GPA did not make a significant difference in the coefficients of interest in our sample, we obtained similar results.

4.3. Comparison to subjective use data

Finally, we repeated the analysis in Section 4.2 with self-reported usage and compared to results found with objective usage in Table 2. For self-reported data, we used an 11-item self-report scale (Harris et al., 2020) querying frequency of using common smartphone features, including voice/video calls, text/instant messaging, email, social media use, website use, listening entertainment, video watching, games, reading, and navigation. The measure uses Likert-type responses from "1 = Never" to "6 = Very often." Higher scores indicate more frequent (self-reported) smartphone use in the different domains. First of all, we checked the correlation between Smartphone Use Frequency (Self-Reported) and Averaged Daily Minutes of Smartphone Use (Objectively Reported). The correlation coefficient was 0.01, which suggests almost no association between these two. Furthermore, the correlation coefficient of self-reported usage with averaged daily number of pickups (Objectively Measured) was −0.04 and with the average daily number of notifications (Objectively Measured) was 0.02. Moreover, self-reported usage was not significant in the regression analysis. These results attest to prior work on low convergence between self-reported estimation of smartphone use frequency and objective use (Ryding & Kuss, 2020).

4.4. Supplementary analysis: a detailed look on the diverse smartphone activities and productivity

Fewer participants ($n = 59$) submitted categories of use screenshots to us, e.g., social networking, gaming, etc. Given the small sample size, instead of computing regression models, we calculated correlations. The appendix table presents Pairwise Correlations with current GPA for the sub-sample with valid Screentime data. Social networking and total hours of daily phone use had a large and statistically significant negative correlation with GPA and self-reported productivity measures. Time spent on social networking negatively correlated with having a sense of accomplishment from school, feeling things got done at school, and sense of accomplishment at school. Time spent on entertainment also had some negative effect on productivity. On the other hand, the number of phone pickups and notifications received were not significantly correlated with GPA or measures of productivity.

5. Discussion

The influence of smartphone use on college students' performance and grades has received growing attention in the literature, which almost exclusively relied on self-reported measures of smartphone use. This paper looks at the association between smartphone use and academic success among college students while controlling for several confounding factors. Using objective and detailed measures of the intensity of smartphone use, we found a significant negative relationship between the time spent on smartphones and college student academic performance. In particular, an additional hour spent using iPhone reduced current term GPA by approximately 0.13–0.18 points and this effect was robust to including different sets of controls and to restricting the sample to the subset of students who submitted category level screenshot data. The negative relationship between time on smartphones and academic performance is further corroborated by an additional finding that time spent on smartphones significantly lowered the probability of reporting getting important things done at school, being satisfied with school achievements and having a sense of accomplishment from school. When examining components of time spent on one's phone, time spent on creativity apps and social networking were associated with significantly lower GPA. In addition, creativity, social networking and entertainment apps lowered the self-reported measures of schooling productivity.

Our findings can be explained within the context of the cognition models described above. In particular, our findings can be explained by the threaded cognition model, clarifying cognitive resource limitations resulting from competing task activity and multitasking. In this model, interruptive smartphone use may interfere with some students' reading and schoolwork completion and consequently reduce available capacity. Furthermore, smartphone use especially if intruding into work or school time may result in poor time management, decreased productivity, and lower grades. Additionally, smartphone use may encourage and facilitate increased surface learning and procrastination, which may lead to lower GPA. Furthermore, intensive smartphone use can be an indicator of a high preference for leisure, which is another plausible explanation for the underlying mechanism of the association between smartphone use and academic performance.

Our empirical results are in line with the growing empirical literature which finds that excessive smartphone use is associated with lower academic performance and less time spent studying (Hawi & Samaha, 2016; Jacobsen & Forste, 2011; Judd, 2014; Karpinski et al., 2013; Lepp et al., 2014; Rosen et al., 2013; Runyan et al., 2013; Wentworth & Middleton, 2014). Furthermore, we have confirmed that results might differ when using subjective measures instead of objective measures. Unlike previous studies, our use of iPhone's ScreenTime feature allows to objectively measure how much time students spent in various categories and allows us to uncover the independent contribution of each category of smartphone use to the reduction in academic performance. For example, spending time in entertainment and social networking (apps and sites like Facebook and Twitter) each had an independent and substantial negative relationship with college GPA. Our finding of the negative relationship between time spent on social networking and GPA is also consistent with previous studies on the relationship between social networking and grades (Wood et al., 2012; Junco, 2012; Judd, 2014; see also a work linking problematic social media use to lower productivity, Rozgonjuk et al., 2020).

It is also important to discuss the generalizability/replicability of our study. Our estimated effect of phone use time on GPA from the regression analysis is within the range of the existing empirical literature. However, correlation coefficients between smartphone time and GPA for the full and subsamples are among the higher end of estimates from the existing studies. Furthermore, the only other coefficient that had a higher correlation with GPA is ACT scores. Non-cognitive, non-ability factors such as parents' income, race, going out for fun, study time, and study habits had correlations in the 0.15–0.20 range similar to the previous literature. More importantly, we found that self-reported phone use had much smaller correlation with GPA than objectively measured phone use. These factors led us believe that the relatively high correlations between GPA and objectively measured phone time are due to the relatively unique "phone use" measure that we used rather than being a sample or variable problem. Our other self-reported variables that we have in the survey had smaller correlations with GPA as in the literature. However, other researchers should investigate the associations of academic performance with objectively measured variables and replicate our results for a definitive conclusion.

While our paper contributes to the literature by using objective measures of time spent on smartphone and on the categories of smartphone use, our study did not collect information on the time of day of phone use. As discussed in Frost et al. (2019), smartphone effects on cognition (including attention) are short lived and only appear as usage levels change. Using smartphones in class and using at home might have different implications for learning and academic performance and future studies can look at this margin. In addition, the data collection for the study was prior to the pandemic and the focus of this study is on the negative impact of smartphone use on academic performance. However, it should be noted that there are also positive aspects of technology on students` wellbeing, and therefore academic success particularly as a result of isolation during the COVID-19 pandemic. Therefore, the impact of smartphone use may be moderated under different conditions, including social isolation, and this should be counted as a limitation and an opportunity for future research. Future studies can also include other sources of distraction besides smartphone. We acknowledge that our study is based on a small sample, future studies should replicate our findings with a larger sample size and also examine the mechanism of the relationship between smartphone use and grades and investigate which aspects of student learning are impacted most by phone use. In addition, future studies should collect experimental data in order to establish the causal link between smartphone use and academic performance. As with any observational study, our empirical approach is subject to criticism and thus it is prudent to regard our estimates as demonstrating strong association by using adjusted correlations between smartphone use time and academic performance rather than demonstrating a direct effect. If more evidence from future studies confirms our findings, the resulting body of literature may lead readers to infer causality.

Declaration of competing interest

None.

Appendix A. Correlation tables

Pairwise Correlation table for the full sample, $N = 99$.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Current GPA	1							
(2) Hrs of daily phone use	−0.32*	1						
(3) ACT score	0.46*	0.01	1					
(4) Total credit hours	0.14	−0.04	0.13	1				
(5) White	0.25*	−0.26*	0.38*	0.04	1			
(6) Productivity 1	0.29*	−0.27*	0.14	−0.05	0.16	1		
(7) Productivity 2	0.38*	−0.14	0.11	−0.04	0.11	0.7*	1	
(8) Productivity 3	0.37*	−0.29	0	−0.04	0.11	0.67*	0.77*	1

[*] $p < 0.01$, Statistical significance, two-sided testing.

Pairwise Correlation table for the sub-sample with valid Screentime data. $n = 59$.

Variables	Current GPA	Productivity 1	Productivity 2	Productivity 3
Hours of daily phone use	−0.30**	−0.25**	−0.24**	−0.31**
Screentime-Creativity (hrs/d)	−0.11	−0.09	−0.15	−0.22
Screentime-Education (hrs/d)	−0.06	0.07	0.07	0.09
Screentime-Entertainment (hrs/d)	−0.11	−0.26**	−0.1	−0.21
Screentime-Games (hrs/d)	−0.08	−0.17	−0.23	−0.21
Screentime-Productivity (hrs/d)	−0.03	−0.08	0.12	0.02
Screentime-Reading (hrs/d)	0.11	−0.02	0.03	0.13
Screentime-Social network. (hrs/d)	−0.36*	−0.27**	−0.26**	−0.33*
Screentime-Other (hrs/d)	−0.16	−0.12	0.05	0.1
Pickups daily average (n/100)	0.05	0.07	−0.09	−0.13
Notifications daily average (n/100)	0.05	0.08	0.001	−0.14
ACT score	0.49*	0.12	0.17	0.07
Tot Credit Hrs	0.18	−0.05	0.05	−0.01
White	0.26**	0.17	0.1	0.1
Productivity 1	0.36*	1	0.72*	0.63*
Productivity 2	0.45*	0.72*	1	0.79*
Productivity 3	0.42*	0.63*	0.79*	1

[*] $p < 0.01$. statistical significance, two-sided testing.
[**] $p < 0.05$. statistical significance, two-sided testing.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2021.102035.

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