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Smartphone Use and Daily Cognitive Failures: A Critical Examination Using a Daily Diary Approach with Objective Smartphone Measures

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Abstract

While smartphones have brought many benefits and convenience to users, there is continuing debate regarding their potential negative consequences on everyday cognition such as daily cognitive failures. A few cross-sectional studies have found positive associations between smartphone use and cognitive failures. However, several research gaps remain, such as the use of a cross-sectional design, confounds related to stable individual differences, the lack of validity in self-report measures of smartphone use, memory biases in retrospective self-reports, and the lack of differentiation between smartphone checking and smartphone screen time. To simultaneously address the aforementioned shortcomings, the current study examined the within-person associations between various objective indicators of smartphone use and daily cognitive failures using a 7-day daily diary study. Multilevel modeling revealed that smartphone checking, but not total smartphone screen time, predicted a greater occurrence of daily cognitive failures at the within-person level. Surprisingly, we also found negative within-person associations between smartphone screen time for social- and tools-related applications and daily cognitive failures, suggesting that some types of smartphone use may temporarily benefit one's cognitive functioning. This finding demonstrates the importance of studying the specific functions of smartphone use and their differential cognitive consequences, as well as highlights the complex relations between smartphone use and cognition.

Keywords: smartphone use, cognitive failures, diary study, objective measure, diary study

Smartphone Use and Daily Cognitive Failures: A Critical Examination Using a Daily Diary Approach with Objective Smartphone Measures

Smartphone use is increasingly ubiquitous in our daily lives; the number of users worldwide rose to a record-breaking 3.6 billion in 2020 and is expected to reach 4.5 billion by 2024 (Gu, 2021). This mounting ubiquity of smartphones is not surprising, as the growing functional adaptability and portability of smartphones make them a highly desirable and immersive technological tool that affords social, informational, and leisure conveniences free from locational restrictions. Accompanying people's habitual and frequent involvement with smartphones, however, is continuing debate regarding possible negative consequences of smartphone use (Harris et al., 2020).

One negative consequence of smartphone use that has received much attention is that in relation to cognition. Smartphones have been argued to be a constant source of distraction that interferes with one's task performance (Throuvala et al., 2021; Wajcman & Rose, 2011). Furthermore, there is research evidence demonstrating that smartphones are used to supplant thinking and induce cognitive miserliness (Barr et al., 2015). From phone books and calendars to gaming devices and internet portals, the integration of a diverse array of applications within a single smartphone supplements a limitless range of cognitive activities. For instance, rather than having to memorize a string of phone numbers or recall upcoming appointments, with a smartphone, people no longer have to dedicate mental effort to carry out these activities. This may encourage people to use smartphones more often to engage in cognitive tasks (for a review, see Wilmer et al., 2017). Indeed, a number of research has found that excessive smartphone use is associated with deficits in inhibitory control (Chen et al., 2016; Hartanto & Yang, 2016), poorer performance on sustained attention tasks and reasoning tasks (Pluck et al., 2020), shortened attention span and lower numerical processing capacity (Hadar et al., 2017), and weaker impulse control (Wilmer & Chein, 2016). While these studies showed that excessive smartphone use is negatively correlated with cognitive functioning, they often assess an individual's cognitive performance at a single timepoint in a laboratory setting that lacks ecological validity and fail to account for how smartphone use may also have momentary effects on people's everyday cognitive functioning. Moreover, there are also a few studies that failed to find strong evidence supporting the effect of smartphone use on cognitive performance, (e.g., Frost et al., 2019; Hartmann et al., 2020), further highlighting the complexity of the relationship between smartphone use and cognitive functions.

An area that warrants further examination is the phenomenon of daily cognitive failures, which refers to cognitive-based errors that occur during ongoing tasks that a person is normally capable of completing (Wallace et al., 2002). Cognitive failures are commonly classified into four categories (Wallace et al., 2002), namely memory (e.g., forgetting which way to turn on a road one knows well but rarely uses), distractibility (e.g., starting on one activity and getting distracted by another), blunders (e.g., saying a statement which one later realizes could have been perceived as insulting to one's conversation partner), and names (e.g., forgetting people's names). Research has showed that daily cognitive failures can be detrimental and are associated with many important negative outcomes such as daily stress (Mahoney et al., 1998), burnout (Linden et al., 2005), workplace accidents (Day et al., 2012; Wallace & Vodanovich, 2003), and traffic accidents (Larson & Merritt, 1991). Despite the importance of daily cognitive failures as a cognitive outcome, only a few studies have examined the relationship between smartphone use and the incidence of daily cognitive failures (Hadlington, 2015; Hong et al., 2020; Marty-Dugas et al., 2018). While these studies have found positive associations between smartphone use and cognitive failures, several research gaps remain.

Firstly, many of the previous studies have not controlled for important variables and relied on between-person association to study the link between smartphone use and cognitive functions (e.g., Al-Khlaiwi et al., 2020; Chen et al., 2016; Ragupathi et al., 2020; Wilmer & Chein, 2016), thus susceptible to myriad confounds related to individual differences. For example, socioeconomic status (SES) can potentially confound the relationship between smartphone use and cognitive functions as SES has been shown to be negatively associated with smartphone use (e.g., Rahmati et al., 2012) while being positively associated with cognitive development (e.g., Hartanto, Toh, & Yang, 2019; Raizada & Kishiyama, 2010). Similarly, trait neuroticism may also serve as a confound as individuals with high trait neuroticism are more likely to excessively use smartphones (Lei, 2020) and at the same time, neuroticism is associated with high incidences of cognitive failures (Flehmig et al., 2007). Thus, there is a need to ensure that the association between smartphone use and cognitive failures is not simply an artefact of confounds related to individual differences.

Secondly, previous studies have relied on self-report measures of smartphone use, which have been shown to be biased and unreliable (Ellis et al., 2019; Hartanto, Quek, Tng, & Yong, 2021). Due to the retrospective nature of such measures, self-reported smartphone use is vulnerable to a host of recall biases and memory distortion. For instance, retrospective recall is likely to be influenced by one’s current physical or mental state and the process of summarizing one’s smartphone use into a single figure itself may also introduce recency effects and availability bias (Stone et al., 2000). Moreover, excessive smartphone use has been found to be automatic in nature, such that users are often unaware of the extent to which they are picking up their smartphones nor are they aware of how long they spend on their devices (Wilcockson et al., 2018). As a result, these behaviors are reported with less accuracy, particularly when it comes to estimating the number of single interactions with their smartphone within a 24-hour period (Andrews et al., 2015). Indeed, numerous recent studies have shown weak correlations between self-reported and objective measures of smartphone use (Lee et al., 2021; Kaye et al., 2020; Parry et al., 2021; Wilcockson et al., 2018).

Thirdly, past studies have focused heavily on total screen time use, which refers to the overall number of hours of smartphone use per day (Lee et al., 2021). As a result, there is a dearth of literature regarding the cognitive consequences of different types of smartphone use. Given that smartphones have evolved over the years to have different functions ranging from communication to social media and entertainment, it is plausible that the use of smartphones for different purposes may have differential effects on cognitive failures in daily life. For instance, the use of social applications on a smartphone may trigger more notifications that can distract one's task performance and increase the incidence of cognitive failures. On the other hand, smartphones provide quick access to tools such as reminders or calculators that can ease cognitive load, thereby reducing the incidence of cognitive failures (Sharifian & Zahodne, 2020). Thus, the mere assessment of a general relationship between total smartphone screen time and cognitive failures may be insufficient in attempting to provide a complete understanding of this phenomenon.

Lastly, existing studies have not accounted for smartphone checking behaviors, which refers to the number of times a user has picked up their smartphone device. While previous studies have focused mostly on smartphone use as measured by screen time, smartphone checking may have unique consequence on cognitive failures due to its distracting nature (Heitmayer & Lahlou, 2021). For instance, engaging in smartphone checking can cause distraction by disengaging users from their ongoing task and redirecting their attention to their smartphones. As smartphone checking occurs regularly, the constant task-switching between the ongoing task and smartphone use may incur switching costs and increase cognitive load, leading to a higher incidence of cognitive failures (Ralph et al., 2014). This suggests that smartphone checking behavior is another indicator of smartphone use that should be studied in relation to daily cognitive failures.

Taken together, the current study aimed to fill the aforementioned research gaps in the literature of smartphone use and cognitive failures by using a daily dairy approach with objective measures of smartphone use. Across a seven-day daily diary study, we collected data on objective smartphone screen time and objective smartphone checking to address limitations related to self-report smartphone use measures (Parry et al., 2021; Wilcockson et al., 2018). To examine possible cognitive consequences of different types of smartphone use, we also collected data on various categories of objective smartphone screen time (i.e., what types of applications are used during smartphone use), such as social, tools, spending, entertainment and games, and health. In addition, cognitive failures were measured on a daily basis to minimize memory biases in retrospective self-reports, and to provide more an ecologically valid assessment of cognitive failures (Almeida et al., 2002). More importantly, by repeatedly administering our measures over a week, the daily diary approach allowed us to examine within-person associations between objective smartphone use and cognitive failures and rule out personality and environmental variables that are stable over time as confounding variables (Almeida et al., 2002). Taken together, based on previous studies that have suggested smartphones as a source of distraction and a supplanter for thinking (Barr et al., 2015; Throuvala et al., 2021), we hypothesized that higher levels of smartphone screen time and checking would each uniquely predict a higher incidence of daily cognitive failures at the within-person level.

Method

Participants

Smartphone users (*N*=261) from a local university were recruited in exchange for monetary compensation of up to $65. The study was conducted as part of a large-scale study examining daily stressors, well-being, and cognitive functions. In order to standardize the screen time tracking system across all participants, we used data from a subset of 183 participants who used an iPhone. Of the 183 iPhone users, one participant withdrew from the study. Another participant reported sharing his smartphone with friends and family, hence any smartphone-related measures gained from this participant would not offer an accurate representation of the participant's smartphone behavior, and as such this participant was removed from the current analyses. After the exclusion of the two participants, there was an overall sample of 181 participants (77.85% female, aged 19–27), with a total of 1,230 observations of daily data (*M*=6.80 days per participant; 97.08% response rate).

The main study consisted of a baseline session and seven days of daily diary surveys. First, participants were required to complete a baseline survey where person-level measures were collected. One or two days later, participants were allowed to proceed to the seven-day daily diary portion. For each of the daily surveys, participants were to complete the survey within a stipulated time window (i.e., from 8.00pm to 3.00am the next day). Data collection was approved by the Institutional Review Board at the authors' university [IRB-20-118-A075(920) & IRB-20-118-A075-M3(121). Written informed consent was obtained from all participants prior to data collection. All participants also provided consent to the collection of data from their personal smartphones. A summary of the descriptive statistics of the sample analyzed in the current work can be found in Table 1.

Table 1

Demographics, Smartphone Checking, Smartphone Screen Time, and Other Characteristics of Participants

	N	*M* (or %)	(*SD*)	Observed Range	Theoretical Range
Person Level					
Demographics					
Race (% Chinese)	181	84.53%			
Sex (% female)	181	77.35%			
Age	181	22.22	1.62		19.00 – 27.00
Monthly household income [a]	181	3.14	1.48	1 – 6	1.00 – 6.00
Subjective socioeconomic status[b]	181	6.23	1.33	0 – 10	3.00 – 9.00
Day Level [c]					
Daily cognitive failures	1229	0.42	0.50	0 – 3	0.00 – 3.00
Daily smartphone checking (number of times)	1229	147.05	71.43		0.00 – 411.00
Smartphone Use (hours)					
Daily total screen time	1229	6.21	2.60		0.00 – 16.20
Daily social screen time	1229	2.43	1.18		0.00 – 8.03
Daily tools screen time	1229	0.50	0.65		0.00 – 7.10
Daily spending screen time	1229	0.60	0.68		0.00 – 6.93
Daily entertainment and games screen time	1229	1.31	1.68		0.00 – 11.82
Daily health screen time	1229	0.03	0.06		0.00 – 0.93
Daily others screen time	1229	0.26	0.61		0.00 – 9.15
Well-Being					
Daily stressor exposure (% of days)	1229	27.18%			
Daily positive affect	1229	2.05	0.88	0 – 4	0.00 – 4.00
Daily negative affect (square root transformed)	1229	0.60	0.45	0 – 2	0.00 – 2.00

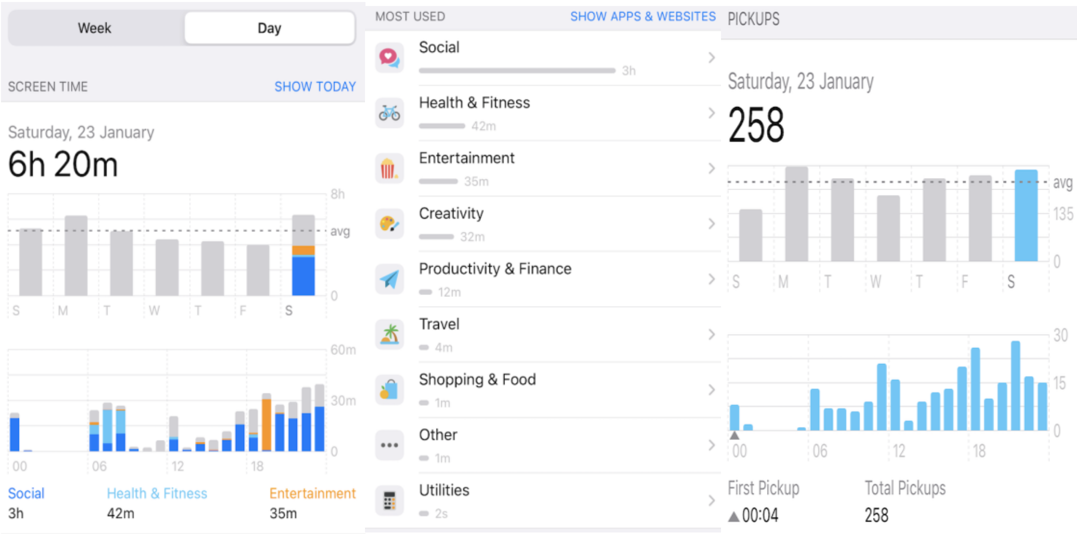
Note. [a] Monthly household income was measured on a 6-point scale (1=*Less than $2,000*, 2=*$2000 – $5999*, 3=*$6000 – $9999*, 4=*$10,000 – $14,999*, 5=*$15,000 – $19,999*, 6=*More than $20,000*). [b] Subjective socioeconomic status was measured on a 10-point scale (0=*Lowest subjective socioeconomic status*, 10=*Highest subjective socioeconomic status*). [c] For day-level variables, *N* refers to the number of observations.

Measures

Objective Smartphone Use. Objective smartphone screen time and smartphone checking for seven days were assessed and tracked via the inbuilt iOS Screen Time Application Programming Interface (Apple Inc., 2019), which has been shown to be reliable and valid (Ohme et al., 2021). During the daily diary study, participants were required to provide screenshots of (i) total screen time, (ii) screen time for each category, and (iii) smartphone checking (see Figure 1 for an example). To ensure that participants were submitting data for the same days of the week across the duration of the study, participants were clearly instructed at the beginning of the study, to upload screen shots of their Screen Time Application Programming Interface of the previous day or two days prior, corresponding to when they are attempting the daily surveys. For instance, if a participant were to be attempting Day 1 of the daily survey, on Tuesday (8pm – 11.59pm), they would then scroll back one day on the application to reveal data collected for the entirety of Monday. In another scenario, if a participant were to be attempting Day 1 of the daily survey on Wednesday (12am – 3am), they would then scroll back two days on the application to reveal data collected for the entirety of Monday. In all cases, participants attempting Day 1 (Tuesday – Wednesday) of the daily survey would be uploading screen shots of Monday's screen time data. We thus collected screen shots from participants for eight days, to fully capture a week's worth of screen time data from every participant. On the eighth day, the online survey consisted only of upload entries for the participants to upload their screen shots. All the screenshots were then manually coded for analysis purposes.

Figure 1.

Samples of Screenshots from the Inbuilt iOS Screen Time Application Programming Interface



Based on the application, we collected screen time for 11 categories, namely: social, utilities, entertainment, games, productivity and finance, creativity, travel, shopping and food, health and fitness-related, information and reading, and others. Applications were by default classified into these categories when developed and uploaded in the App Store. All of our participants were required to use the default categorization to ensure comparability. As there were significant overlaps between the functionalities of the categories, some categories were further merged. For example, *entertainment* and *games* were grouped together and renamed *entertainment and games*, as the applications in these two categories are used for entertainment purposes. Similarly, *utilities*, *creativity*, *travel*, and *information and reading* were grouped together and renamed *tools*, as the applications in these four categories are tools which assist users to perform certain tasks (Apple Inc., 2021). In total, six screen time categories were created, which consisted of social, entertainment and games, tools, spending, health, and others. A summary of the categories can be found in Table 2.

Table 2

Summary of the Screen Time Categories, Details, and Examples

Category	Consists of	Examples
Social	Social related applications	Facebook, Instagram, WhatsApp, Telegram
Entertainment and Games	Entertainment and games applications	Netflix, YouTube, Candy Crush
Tools	Utilities, creativity, travel, and information and reading applications	Calculator, Camera, Google Maps, Strait Times News
Spending	Finance-, shopping-, food- and productivity- related applications	American Express, McDonald's, Amazon
Health	Health and fitness-related applications	Great Eastern Life, HealthHub
Others	Other applications not relevant to the above categories	Safari

Cognitive Failures. The incidence of daily cognitive failures was assessed by the 13-item Cognitive Failures in Everyday Life Scale (Lange & Süß, 2014). For seven days, participants rated their agreement with a series of statement about their everyday cognitive failure on that day (e.g., "did you leave a task unfinished due to distraction(s), at any point of time today?", "couldn't remember the right word, at any point of time today?", "did your mind unintentionally wander, at any point of time today?") on a four-point Likert scale (0=*Never,* 3=*Several times*). Daily cognitive failure scores were calculated by averaging the items in the scale ($\alpha_{seven\text{-}days}$=[.87, .90]). Higher scores on the scale indicate a greater incidence of daily cognitive failures.

Daily Stressor Exposure. Daily stressor exposure was assessed by the Daily Inventory of Stressful Events (Almeida et al., 2002). The measure consists of seven types of stressors, including discrimination, work/education stressors, network stressors, arguments, avoided arguments, stressors at home, and others. Participants reported whether they experienced any of the seven stressors in the daily diary study. If they reported at least experiencing at least one of the stressors, the day was recorded as a stressor day.

Daily affect. Positive affect and negative affect were assessed using the Daily Distress Scale developed by Morczek and Kolarz (1998). Participants rated how frequently they felt 13 positive affect items (e.g., “cheerful”, “enthusiastic”) during the day on a four-point scale (0=*none of the time*, 4=*all of the time*). Daily positive affect was computed by averaging the 13 items ($\alpha_{seven\text{-}days}$=[.95, .97]). Similar to positive affect, participants rated how frequently they felt 14 negative affect items (e.g., “lonely”, “afraid”) during the day (0=*none of the time*, 4=*all of the time*). Daily negative affect was computed by averaging the 9 items ($\alpha_{seven\text{-}days}$=[.93, .95]). To reduce skewness in the negative affect scores, a square-root transformation was performed.

Demographics. During the baseline survey, participants reported their demographics such as age, sex, monthly household income, and subjective socioeconomic status. Monthly household income was measured using a single item (1=*less than $2000*, 2=*$2000-$5999*, 3=*$6000-$9999*, 4=*$10,000-$14,999*, 5=*$15,000-$19,999*, 6=*more than $20,000*). Subjective socioeconomic status was assessed by the MacArthur Scale (Adler et al., 2000), which uses an image of a ladder on which participants indicate their self-perceived social standing in their community by choosing the most appropriate rung on the ladder ranging from 1 (*lowest standing*) to 10 (*highest standing*).

Analytic Plan

As the nature of the study includes repeated measures across multiple participants, multilevel modeling (Cole et al., 2020) was used to account for the nested data structure to investigate whether smartphone use indicators—smartphone checking, total screen time, and screen time for each category—predicted the incidence of daily cognitive failures. Repeated measures over the course of seven days (Level 1) were nested within participants (Level 2). Both unadjusted and adjusted models were estimated. The first model was an unadjusted model testing the relationship between smartphone use and cognitive failures without covariates. The adjusted model controlled for participant-level demographics factors such as age, sex, monthly household income, and subjective socioeconomic status. In order to account for within-person fluctuations in daily stress and affective states as potential confounds, we also controlled for stressor exposure, positive affect, and negative affect (Lee et al., 2020; Majeed et al., 2021) in our adjusted model at Level 1 (i.e., daily) and Level 2 (i.e., person-level averages). All non-binary variables measured at Level 2—age, monthly household income, subjective socioeconomic status were grand-mean centered while daily positive affect and negative affect were person-mean centered with their person means reintroduced at Level 2. As such, the equations for the final model are as follows:

Level 1: (Daily cognitive failures)$_{di}$=B_{0i} + B_{1i} (daily smartphone use)$_{di}$

+ B_2(daily stressor exposure)$_{di}$ + B_3(daily positive affect)$_{di}$ + B_4(daily negative affect)$_{di}$ + ε_{di}

Level 2: B_{0i}=γ_{00} + γ_{01}(average smartphone use)$_i$ + γ_{02}(age)$_i$ + γ_{03}(sex)$_i$

+ γ_{04}(monthly household income)$_i$ + γ_{05}(subjective socioeconomic status)$_i$

+ γ_{06}(average stressor exposure)$_i$ + γ_{07}(average positive affect)$_i$

+ γ_{08}(average negative affect)$_i$ + μ_{0i}

B_{1i}=γ_{10} + μ_{1i}

At Level 1, B_{0i} is the intercept indicating participant i's average cognitive failures with no smartphone use, while B_{1i} shows participant i's change in daily cognitive failures in relation to increases in smartphone use. B_2, B_3, *and* B_4 measure participant i's change in cognitive failures in response to stressor exposure, positive affect, and negative affect respectively. At Level 2, the intercept coefficient B_{0i} for each participant *i* was modelled as a function of between-person differences. This includes participant *i*'s average smartphone use over the duration of 7 days, and other person-level covariates (i.e., age, sex, monthly household income, subjective socioeconomic status, average stressor exposure, average positive affect, and average negative affect). The deviation of each individual's intercept and slope from the model-implied values are indicated by μ_{0i} and μ_{1i} respectively. Separate multilevel model analyses were run for each smartphone use indicators: smartphone checking, screen time and each screen time category.

Transparency and Openness

The design and analytic approach for the present research were not pre-registered. Data and analytic code have been made publicly available on Researchbox (#628; https://researchbox.org/628&PEER_REVIEW_passcode=QJKQOF). Multilevel modeling and analysis were conducted in R version 3.6.3 (R Core Team, 2020) using lme4 version 1.1–23 (Bates et al., 2014) and lmerTest version 3.1–2 (Kuznetsova et al., 2017). To prevent convergence failures, bobyqa optimization was used with a maximum of 10,000,000 evaluations. When the model failed to converge, random slope of the respective smartphone use indicator for each participant was removed from the model. With the exception of the models predicting daily cognitive failure based on smartphone screen time for social and tool-related applications, the random slope of the respective smartphone use indicator for each participant was removed from the remaining models which failed to converge.

Results

Smartphone Checking

We first examined the within-person association between smartphone checking and daily cognitive failures. The results showed that daily smartphone checking significantly and predicted higher levels of daily cognitive failures at the within-person level in the unadjusted model (β=.05, γ_{10}=0.001, *SE*=0.0002, 95% CI=[0.0002, 0.0010], *p*=.003) to a small extent. More importantly, even after controlling for age, sex, monthly household income, subjective socioeconomic status, daily stressor exposure, daily positive affect, and daily negative affect in the adjusted model, smartphone checking remained as a significant predictor of higher levels of daily cognitive failures at the within-person level (β=.04, γ_{10}=0.0004, *SE*=0.0002, 95% CI=[0.00005, 0.00080], *p*=.025; see Table 3).

Table 3

Multilevel Modeling Results for Daily Smartphone Checking in Predicting Daily Cognitive Failure

	Unadjusted Model		Adjusted Model	
	Std. Coeff.	Coeff. (*SE*)	Std. Coeff.	Coeff. (*SE*)
Fixed Effects				
Intercept, γ_{00}	.00	0.38 (0.09)***	-.00	0.07 (0.47)
Daily smartphone checking, γ_{10}	.05	0.0006 (0.00)**	.04	0.0004 (0.00)*
Average smartphone checking, γ_{01}	.03	0.00 (0.00)	.04	0.00 (0.00)
Covariates				
Age, γ_{02}			-.01	0.00 (0.02)
Sex, γ_{03}			-.10	-0.12 (0.06)
Monthly household income, γ_{04}			.06	0.02 (0.02)
Subjective socioeconomic status, γ_{05}			-.01	-0.00 (0.02)
Daily stressor exposure, B_2			.09	0.10 (0.03)***
Average stressor exposure, γ_{06}			.17	0.33 (0.10)**
Daily positive affect, B_3			.03	0.03 (0.02)
Average positive affect, γ_{07}			-.03	-0.02 (0.04)
Daily negative affect, B_4			.14	0.26 (0.04)***
Average negative affect, γ_{08}			.38	0.54 (0.08)***
Random Effects				
Intercept, μ_{0i}	.61	0.16	.35	0.09

Daily smartphone checking, μ_{1i}				
Residual, ε_{di}	.39	0.10	.35	0.09

Notes. Random slope of daily smartphone checking (μ_{1i}) was removed from the model as the model failed to converge. ***$p < .001$, **$p < .01$, *$p < .05$

Smartphone Screen Time

A series of multilevel models were estimated to examine the within-person associations between smartphone screen time and daily cognitive failures. For total smartphone time, we found a significant negative within-person association between daily total smartphone screen time and incidences of daily cognitive failures in the unadjusted model (β=-.04, γ_{10}=-0.01, *SE*=0.01, 95% CI=[-0.022, -0.002], *p*=.019). However, the within-person association between daily total smartphone screen time and incidences of daily cognitive failures was not significant in the adjusted model (β=-.03, γ_{10}=-0.01, *SE*=0.01, 95% CI=[-0.0194, 0.0003], *p*=.057). The results suggest that total smartphone screen time was not a robust predictor of daily cognitive failures.

To further probe the predictability of smartphone screen time on incidences of daily cognitive failures, multilevel modeling was conducted for each smartphone screen time category, namely social, entertainment and games, tools, spending, health and other. In the unadjusted model, we found that incidences of daily cognitive failures were only significantly predicted by smartphone screen time for social-related applications (β=-.05, γ_{10}=-0.03, *SE*=0.01, 95% CI=[-0.054, -0.010], *p*=.006) and tools-related applications (β=-.04, γ_{10}=-0.05, *SE*=0.02, 95% CI=[-0.090, -0.003], *p*=.036) but not for spending-related applications (β=.02, γ_{10}=0.02, *SE*=0.02, 95% CI=[-0.013, 0.054], *p*=.227), entertainment and games-related applications (β=-.01, γ_{10}=-0.01, *SE*=0.01, 95% CI=[-0.021, 0.009], *p*=.427), health-related applications (β=-.00, γ_{10}=-0.02, *SE*=0.20, 95% CI=[-0.409, 0.369], *p*=.918), and other applications (β=-.01, γ_{10}=-0.01, *SE*=0.02, 95% CI=[-0.049, 0.023], *p*=.479). Similarly, in the adjusted model, only smartphone screen time for social-related applications (β=-.05, γ_{10}=-0.03, *SE*=0.01, 95% CI=[-0.052, -0.008], *p*=.009) and tools-related applications (β=-.05, γ_{10} =-0.05, *SE*=0.02, 95% CI=[-0.090, -0.010], *p*=.015) remained as significant predictors of daily cognitive failures. The result showed that on days when participants spent more time on social-related applications or tools-related applications, they were less likely to experience cognitive failures, as compared to days when participants spent more time on social-related applications or tools-related applications (see Table 4).

Table 4

Multilevel Modeling Results for Total Screen Time, Social Screen Time, and Tools Screen Time in Predicting Daily Cognitive Failure

	Total Screen Time		Screen Time on Social Applications		Screen Time on Tools Applications	
	Unadjusted Model	Adjusted Model	Unadjusted Model	Adjusted Model	Unadjusted Model	Adjusted Model
	Coeff. (*SE*)	Coeff. (*SE*)	Coeff. (*SE*)	Coeff. (*SE*)	Coeff. (*SE*)	Coeff. (*SE*)
Fixed Effects						
Intercept, γ_{00}	0.35 (0.10)***	0.10 (0.46)	0.46 (0.09)***	0.18 (0.44)	0.44 (0.05)***	0.18 (0.45)
Daily smartphone screen time, γ_{10}	-0.01 (0.01)*	-0.01 (0.01)	-0.03 (0.01)**	-0.03 (0.01)**	-0.05 (0.02)**	-0.05 (0.02)*
Average smartphone screen time, γ_{01}	0.01 (0.02)	0.01 (0.01)	-0.02 (0.04)	-0.02 (0.03)	-0.03 (0.07)	-0.04 (0.05)
Covariates						
Age, γ_{02}		0.00 (0.02)		-0.00 (0.02)		-0.00 (0.02)
Sex, γ_{03}		-0.13 (0.06)*		-0.13 (0.06)*		-0.13 (0.06)*
Monthly household income, γ_{04}		0.02 (0.02)		0.02 (0.02)		0.02 (0.02)
Subjective socioeconomic status, γ_{05}		-0.01 (0.02)		-0.01 (0.02)		0.00 (0.02)
Daily stressor exposure, B_2		0.10 (0.03)***		0.09 (0.02)***		0.10 (0.02)***
Average stressor exposure, γ_{06}		0.35 (0.10)***		0.37 (0.10)***		0.32 (0.10)**
Daily positive affect, B_3		0.03 (0.02)		0.04 (0.02)*		0.04 (0.02)*
Average positive affect, γ_{07}		-0.02 (0.04)		0.01 (0.04)		-0.01 (0.04)
Daily negative affect, B_4		0.53 (0.08)***		0.27 (0.03)***		0.27 (0.04)***
Average negative affect, γ_{08}		0.35 (0.10)***		0.50 (0.07)***		0.55 (0.08)***
Random Effects						
Intercept, μ_{0i}	0.15	0.09	0.16	0.09	0.16	0.09
Daily smartphone screen time, μ_{1i}			0.00	0.00	0.01	0.00
Residual, ε_{di}	0.10	0.09	0.10	0.09	0.10	0.09

Notes. Values reflect coefficient estimates in predicting daily cognitive failures. Standard errors are shown in parentheses. When the model failed to converge, random slope was removed from the model. ****p* < .001, ***p* < .01, **p* < .05

Exploratory Analyses

Subfactors of Cognitive Failures. To speculate the categories of cognitive failure that were driving the significant within-person associations found in the current study, we categorized items in the the Cognitive Failures in Everyday Life Scale into 3 commonly known factors of cognitive failure, namely distractibility, blunders and memory failure. Subsequently, multilevel confirmatory factor analysis using ‘lavaan’ package in R. The multilevel factor model produced acceptable fit metrics, with CFI = .86, TLI = .82, $SRMR_{within}$ = .062, $SRMR_{between}$ = .080, RMSEA = .066, and all factor loadings were statistically significant at $p<.05$. Next, multilevel exploratory analysis was performed with the 3 factors of cognitive failure (i.e., distractibility, blunders and memory) specified as outcomes. In summary, our results suggest that the ‘distractibility’ categories of cognitive failure were likely the main driver of the negative within-person associations found in total smartphone screen time (β=-.04, γ_{10}=-0.02, *SE*=0.01, 95% CI = [-0.031, -0.002], *p*=.025) and smartphone screen time for social-related applications (β=-.05, γ_{10}=-0.04, *SE*=0.01, 95% CI = [-0.07, -0.01], *p*=.004) and tools-related applications (β=-.05, γ_{10}=-0.07, *SE*=0.03, 95% CI = [-0.13, -0.02], *p*=.006). In contrast, the ‘blunder’ categories of cognitive failure were likely the main driver of the positive within-person associations found in smartphone checking (β=.04, γ_{10}=0.00, *SE*=0.00, 95% CI = [0.00003, 0.00077], *p*=.033; see Supplementary Materials for full results).

Affect as Outcome. We also have conducted exploratory multilevel analyses by specifying negative affect and positive affect as outcomes. In summary, most of the within-person associations between smartphone usage indicators (smartphone checking and smartphone screen time) and affective outcomes (positive affect and negative affect) were not significant, with exception for the significant positive within-person association between smartphone checking and positive affect (β=.05, γ_{10}=0.00, *SE*=0.00, 95% CI = [0.0002, 0.0016], p=.011), negative within-person association between total smartphone screen time and positive affect (β=-.07, γ_{10}=-0.04, SE=0.01, 95% CI = [-0.06, -0.02], p<.001), and negative within-person association between positive within-person association between smartphone checking and negative affect (β=.05, γ_{10}=0.00, SE=0.00, 95% CI = [0.00009, 0.00080], p=.014) (see Supplementary Materials for full results).

Discussion

As smartphone use has become increasingly prevalent in our daily lives, there also has been continuing debate regarding the possible negative consequences of smartphone use on daily cognitive functions. While existing studies have found positive association between smartphone use and cognitive failures (Hong et al., 2020; Marty-Dugas et al., 2018), several research gaps remain due to limitations such as the use of a cross-sectional design, confounds related to stable individual differences, the lack of validity of self-report measures of smartphone use, memory biases in retrospective self-reports, and the lack of accounting different smartphone use indicators (e.g., frequency of smartphone checking and duration of smartphone screen time). In consideration of these issues, we sought to investigate the within-person associations between various indicators of smartphone use and the incidence of daily cognitive failures using a daily diary study with objective smartphone measures, thus allowing us to simultaneously address the aforementioned shortcomings of prior research. Several important findings were noteworthy.

Firstly, we found positive within-person associations between smartphone checking and daily cognitive failures in both the unadjusted and adjusted models. The findings demonstrate that on days where participants engaged in more smartphone checking (compared to their own average levels of smartphone checking), they were more likely to experience cognitive failures, as compared to days when participants engaged in less smartphone checking. This is in line with our prediction that smartphone checking is a distracting behavior due to the constant task-switching and disengagement from the ongoing task, leading to an increment in cognitive load and thus cognitive failures. The results are also consistent with the resource theory perspective which states that cognitive errors occur due to limited attentional resources and higher cognitive load (Head & Helton, 2014).

Secondly, in contrast to our findings in relation to daily smartphone checking behaviors, we found negative within-person association between smartphone screen time and incidences of daily cognitive failures. More importantly, negative within-person association was specific to social- and tools-related applications. That is, on days when participants spent more time on social-related applications or tools-related applications, they were less likely to experience cognitive failures, as compared to days when participants spent less time on social-related applications or tools-related applications. Contradicting existing studies (e.g., Hong et al., 2020; Wilmer & Chein, 2016), the current findings suggest that some types of smartphone use can temporarily benefit one's cognitive functioning. This could be attributed to the role that tools screen time play in helping individuals momentarily offload cognitive resources, thereby freeing up mental capacity to work on goal-related tasks and reduces task-related interference (Eysenck et al., 2007). For instance, one of the tools applications, the calculator, may help individuals to calculate the cost of the groceries while they recall what to buy. Applications like Google Maps also remind users of their destinations and show directions. Such tools-related applications help to ease one's cognitive load, which frees up mental capacity for other tasks. However, the negative within-person associations in social-related applications were unexpected. Social-related apps should be distracting as it can encourage more smartphone-checking behaviors and interfere goal-directed behaviors. Nevertheless, due to the small effect sizes, the within-person association between screen time of tools-related apps and incidences of daily cognitive failures could be spurious (Ferguson & Heene, 2021).

Lastly, while robust within-person associations were observed in daily cognitive failures relation to function-specific smartphone screen time on social-related applications or tools-related applications, we found that a generic total smartphone screen time was not a robust predictor of daily cognitive failures. After various important covariates such as daily stressors, daily positive affect, and daily negative affect were controlled for in the analyses, the within-person association between total smartphone screen time and daily cognitive failures became non-significant. The findings suggest that total objective screen time is a crude indicator of smartphone use. Due to the integration of a diverse array of applications within a single smartphone, total screen time may reflect different smartphone behaviors across different users and times, resulting in low reliability. The current findings highlight the importance for future study to move beyond total screen time and focus on each functionality of smartphone in studying their cognitive and socioemotional consequences (Hartanto, Lua, Quek, Yong, & Ng, 2021).

The current study is not without limitations. Although the daily diary method increases the ecological validity of the current study, the correlational nature of the current study limits inferences that can be drawn about the causal relationship between smartphone use and cognitive failures. Future research could investigate the effect of smartphone use on daily cognitive failures using experimental design that manipulates smartphone use abstinence (Hartanto, Quek, Tng, & Yong, 2021). Furthermore, as the current sample included only young adults, more studies should be conducted to examine the generalizability of the current findings to other age groups and cultures. Additionally, the current study was restricted to iPhone users in order to standardize the screen time tracking system across all participants. Future research should attempt to replicate the findings with a more diverse range of smartphone users such as those that are using Android operating system. Lastly, the significant findings observed in the current study should be interpreted with caution given that most of the standardized coefficient betas found were lower than 0.1, suggesting that these effects may lack of interpretive value (Ferguson & Heene, 2021).

Despite the limitations, the rigorous multilevel modeling, longitudinal daily diary design, and objective measures of smartphone use are notable strengths of the current study. The rigorous methodology allows the current study to address confounds related to stable individual differences, increase ecological validity, reduce memory bias, increase the validity and reliability of smartphone use measures, and provide a comprehensive investigation of the relationship between the different categories of screen time and daily cognitive failures at within-person level. More importantly, the negative within-person association between smartphone screen time on social-related applications or tools-related applications and daily cognitive failures disputes existing studies and highlights the complex and interconnected relations between smartphone use and cognition.

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