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Problematic Smartphone Usage, Objective Smartphone Engagement, and Executive Functions: A Latent Variable Analysis

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Abstract

The negative consequences of smartphone usage have seen frequent discourse in popular media. While existing studies seek to resolve these debates in relation to executive functions, findings are still limited and mixed. This is partly due to the lack of conceptual clarity about smartphone usage, the use of self-reported measures, and problems related to task impurity. Addressing these limitations, the current study utilizes a latent variable approach to examine various types of smartphone usage, including objectively measured data-logged screen time and screen-checking, and 9 executive function tasks in 260 young adults through a multi-session study. Our structural equation models showed no evidence that self-reported normative smartphone usage, objective screen time and objective screen-checking are associated with deficits in latent factors of inhibitory control, task-switching, and working memory capacity. Only self-reported problematic smartphone usage was associated with deficits in latent factor of task-switching. These findings shed light on the boundary conditions of the link between smartphone usage and executive functions and suggest that smartphone usage in moderation may not have inherent harms on cognitive functions.

Keywords: smartphone usage, executive functions, structural equation modelling

Introduction

Since the emergence of smartphones in the 1990s, we have witnessed huge lifestyle changes in day-to-day human activities. Smartphones have introduced new and improved ways to communicate, interact with friends, store information, seek entertainment, and consume goods and services, among many other functions. Replacing older technologies such as landlines, MP3 players, radios, and cable television, smartphones have become embedded in the daily lives of most people. To illustrate, as of 2021, the number of smartphone adoptions around the world has surpassed six billion and is estimated to continue to increase for several more years (O'dea, 2021). China, India, and the United States have been marked as the countries with the highest number of smartphone users in the world, and even in Singapore alone, smartphone penetration was as high as 148% in 2020, meaning that on average, each Singaporean owns about 1.5 smartphones (Müller, 2021). The growing functional adaptability and mobility of smartphones make it a highly desirable multi-functionality technological tool unbounded by locational restrictions. Consequently, frequent usage is common among smartphone users. Studies have reported that smartphone users on average spend more than 4 hours daily on their smartphones and routinely check their phones at least 30 times per day (Hartanto & Yang, 2016; Loid, Täht, & Rozgonjuk, 2020; Zhitomirsky-Geffet & Blau, 2016).

Due to the prevalence and pervasiveness of smartphones, there has been growing interest among researchers in understanding the potential implications of smartphone usage. Preliminary studies have provided evidence of the negative short-term effects related to smartphone use. The simultaneous use of media technology, including smartphones, is associated with higher levels of distractibility (Ophir et al., 2009) and a less precise coding of information in the working memory (Uncapher et al., 2015). Smartphone use has also been negatively linked to inferior performance on numeracy, problem-solving, and verbal intelligence tests (Barr et al., 2015), and a diminished tolerance for delayed gratification (Hadar et al., 2015). While smartphone usage implicates various domains of cognition, one domain that has received growing interest is executive functions: a multifaceted construct of higher-order cognitive processes responsible for controlling and regulating thoughts and actions to achieve a goal (Miyake et al., 2000).

It is widely assumed that extensive usage of smartphones may be detrimental to our mental functions due to their distracting nature (Wilmer et al., 2017). Wilmer et al. (2017) highlighted in their review that smartphone distractions can result in poorer task performances because they divert attention away from ongoing tasks and onto our smartphones. Indeed, Leiva et al. (2012) demonstrated that when participants were using their smartphones to complete a task, interruptions from a different application resulted in a resumption lag which can delay the completion of that task by up to four times. Likewise, Stothart et al. (2015) discovered that when participants received notifications from their cellphones, they were more likely to make an error on an attention-demanding task than participants who did not receive any notifications. More recently, Thorton et al. (2014) and Ward et al. (2017) revealed that the mere presence of smartphones was enough to impair attentional and working memory capacity. Ward et al. (2017) also found that the extent of smartphone reliance attenuated the detrimental impact of smartphone salience on working memory capacity. When exposed to the same degree of smartphone salience, participants who were more reliant on their smartphones showed poorer performance on the Automated Operation Span Task compared to participants who were less reliant on their smartphones (Ward et al., 2017). These recent findings prompted researchers to hypothesize that because smartphones are so inextricable to our daily lives, their mere presence distracts us by automatically priming smartphone-related concepts in our minds (Kardos et al., 2018). This unconscious priming process is cognitively costly because it increases our working memory load and depletes cognitive resources as we attempt to inhibit the urge to attend to our smartphones (Schwaiger & Tahir, 2022). While the mechanism in which smartphone distractions affect executive functions remains underexplored, the above studies seem to support the assumption that smartphones have an acute effect on executive functions in the short term due to its distractive nature.

Furthermore, there have also been widespread claims in the popular media that high levels of smartphone use may have lasting impacts on attentional span and executive functions in the long run. Based on the idea of neuroplasticity—the ability of our brain to modify its organization and ultimately its function on the basis of changes in the environment and experience (Kolb, Gibb, & Robinson, 2003; Park & Bischof, 2013)—some have argued that the constant distraction by smartphones as well as the overreliance on smartphones for everyday tasks may alter and weaken the executive functioning of those with high levels of smartphone usage (Merzenich, 2013; Williams, 2019). The study by Choi et al. (2021) provides initial evidence that high levels of smartphone use can modify the structure and function of the brain. Problematic smartphone users' worse performance on an attentional control task compared to the control group was linked to greater activity in brain regions associated with stimulus-driven attentional control (Choi et al., 2021). According to the authors, higher activity in these regions stemmed from the inefficiency of neural circuits among problematic smartphone users. While cross-sectional findings from Choi et al. (2021) cannot be used to conclude that heavy smartphone usage can modify our neural functions and negatively influence our mental processes in the long-term, the impact of extensive smartphone usage on executive functions remains a cause for concern. Given the ubiquity of smartphones and the argument that extensive usage may result in detrimental effects on our mental functions, the discourse on the cognitive consequences of smartphone usage has been featured widely in popular media over time.

Although much focus has been placed on the negative consequences of smartphone usage, the empirical evidence on the relationship between smartphone usage and executive functions has been limited and mostly mixed (Wilmer, Sherman, & Chein, 2017). For instance, in an earlier study with a Go/No-Go task, Chen, Zhang, Zhao, Lee, and Cong (2016) found that problematic smartphone usage was associated with larger N2 amplitudes in No-Go trials, suggesting that problematic smartphone users had general deficits in the early stage of inhibitory control at the neural level. However, Chen et al. (2016) did not find any differences between problematic and non-problematic smartphone users on accuracy or reaction time in the Go/No-Go task. In another study by Wilmer and Chein (2016), mobile technology engagement was not associated with false alarm rates on a Go/No-Go task. Similarly, a longitudinal study by Hadar et al. (2017) reported no significant differences in performance on a stop-signal task between heavy smartphone users and new smartphone users. Interestingly, a recent study by Toh, Ng, Yang, and Yang (2021) found that frequency of smartphone usage predicted better task-switching ability and working memory capacity. Taken together, currently, there is no conclusive evidence that frequent smartphone usage is associated with deficits in executive functions.

The mixed findings in the literature prompted the current study which aimed to revisit the association between smartphone usage and executive functions with several conceptual and methodological improvements. First, we aimed to improve on the conceptual clarity of smartphone usage in the current study by distinguishing normative smartphone usage from problematic smartphone usage, which is characterized by overuse, loss of control, withdrawal symptoms, and daily life disturbance (Busch & McCarthy, 2021; Kwon, Kim, Cho, & Yang, 2013; Pluck, 2020). This distinction is critical due to the possible differential associations of executive functions with problematic smartphone usage compared to everyday mobile technological engagement (Toh et al., 2021). Fundamentally, the motivations behind problematic and normative smartphone usage are different; normative smartphone usage is associated with greater instrumental motivation (e.g., to obtain knowledge or information) compared to problematic smartphone usage which is associated with self-expressive (e.g., to gain acceptance) and hedonic (e.g., to gain pleasure) motivations (Meng et al., 2020). Such differences, if left indistinct, could result in inconsistent findings as pathways leading to the changes in executive functions are not clearly specified. For instance, according to the pathway model of problematic mobile phone usage (Billieux, Maurage, Lopez-Fernandez, Kuss, & Griffiths, 2015), lower levels of executive functioning could simply reflect an antecedent or risk factor leading to, rather than being, the consequence of problematic smartphone usage. Moreover, a recent study by Toh et al. (2021) revealed that problematic and normative smartphone usage asymmetrically correlate with executive functions. Thus, distinguishing everyday mobile technology engagement from problematic smartphone usage may allow us to gain a better understanding of the boundary conditions underlying the association between smartphone usage and executive functions.

Second, the current study strove to measure smartphone usage objectively in addition to using the more common method of self-reported measures of mobile technology engagement and problematic smartphone usage. Existing studies investigating the individual differences of executive functions among smartphone users have mostly relied on self-reported measures where participants were required to retrospectively recall and report their everyday smartphone usage patterns (e.g., Chen et al., 2016; Wilmer & Chein, 2016). However, subjective measures of mobile technology engagement have been shown to be biased and vulnerable to memory distortion (Ellis, Davidson, Shaw, & Geyer, 2019). Additionally, due to the habitual and automatic nature of smartphone usage, most smartphone users are often unaware of how long they spend on their devices (Wilcockson, Ellis, & Shaw, 2018) and this may result in inaccurate reports of actual smartphone usage. Indeed, numerous studies have shown that self-reported smartphone screen time differed significantly from actual smartphone screen time that was measured objectively (Hodes & Thomas, 2021; Parry et al., 2021; Shaw et al., 2020). Thus, an objective data-logged measurement of smartphone usage would allow the current study to address the existing limitations of self-reported smartphone usage measures, thus providing grounds for comparison (i.e., between objective and subjective measures) as well as a more accurate reflection of mobile technology engagement.

Third, the study sought to employ a latent variable approach to address task impurity problems, where studies have consistently reported low intercorrelations among tasks measuring executive functions, due to their involvement of non-executive function processes (Friedman & Miyake, 2004; Miyake et al., 2000). For example, performance on the Go/No-Go task is not purely driven by the ability to inhibit prepotent responses, but also involves visual recognition ability as well as motor skills (De Kleine & Van der Lubbe, 2011; Simmonds, Pekar, & Mostofsky, 2008). The inherent task impurity problem may obscure or inflate the true relation between smartphone usage and executive functions. The use of latent approaches in the current study would allow us to address the task impurity problem by extracting the common variance among multiple tasks assessing executive function, which would exclude idiosyncratic non-executive function processes, resulting in a more precise and reliable measure of executive functions (Friedman & Miyake, 2017; Hartanto & Yang, 2020).

Overall, the use of a latent variable approach along with more refined measures of smartphone use—consisting of self-reported and objective measures of mobile technology engagement as well as problematic smartphone use—allowed us to precisely examine the understudied association between smartphone usage and executive functions. In addition to the latent variable approach, the current study also assessed all three core domains of executive functions—inhibitory control, task-switching ability, and working memory capacity—based on the three-factor model of executive functions (Miyake et al., 2000). As most previous studies have focused on inhibitory control (e.g., Chen et al., 2016; Wilmer & Chein, 2016), testing all domains of executive functions resulted in a study that could provide a more comprehensive understanding of the associations between smartphone usage and other aspects of executive functions beyond inhibitory control.

Method

Participants

The current study consisted of 261 undergraduates from various universities in Singapore as part of a broader study that examined daily experiences and executive functions (e.g., Hartanto et al., 2022, 2023; Lua et al., 2022; Ng et al., 2022). One participant was excluded from the present analyses as the participant did not attend the executive functions session, leaving a total of 260 valid participants. The current sample was larger than the recommended size of 150 for latent variable analysis of latent factors with three or more indicators (Gerbing & Anderson, 1985; Holbert & Stephenson, 2002). The study was conducted with approval from the Institutional Review Board at the authors' university, and participants provided informed consent to participate in the study in return for compensation of up to S$65. Materials and subject-aggregated data have been made publicly available on Researchbox (#330) at https://researchbox.org/330.

Measures

Smartphone Usage Measures

Self-Reported Problematic Smartphone Usage. Self-reported problematic smartphone usage was assessed by a 10-item Kwon's et al. (2013) Smartphone Addiction Scale–Short Version (SAS-SV). Participants rated their agreement with a series of statements about their problematic smartphone usage (e.g., missing planned work due to smartphone usage; having a hard time concentrating in class, while doing assignments or while working due to smartphone usage) on a 6-point Likert scale (1 = *strongly disagree* to 6 = *strongly agree*).

Self-Reported Normative Smartphone Usage. Self-reported normative smartphone usage was assessed by an 8-item mobile technology engagement scale developed by Wilmer and Chein (2016). The scale was designed to assess three aspects of normative smartphone usage: usage of social media applications (e.g., if Facebook is installed on your phone, how much time do you spend using it daily), frequency of status updates (e.g., how often do you post public updates), and smartphone-checking activity (e.g., how often do you find yourself checking your phone during conversation or when hanging around with friends).

Objective Screen Time and Screen-Checking. Two indicators of objective smartphone usage were assessed: objective screen time and objective screen-checking. Data on each indicator was collected from each participant daily over 8 days. During the baseline session, participants were required to download a smartphone application to record their screen time and frequency of screen-checking daily over 8 days. A physical briefing session was conducted to guide the participants and ensure that the application was installed appropriately. For iPhone users, both indicators (screen time and frequency of screen-checking) were monitored via the inbuilt iOS Screen Time interface, which has been shown to be reliable and valid (Ohme, Araujo, De Vreese, & Piotrowski, 2021). Objective screen-checking was measured by how often the participants picked up their phones as shown in the Total Pick-Up per day shown in the Screen Time interface. For Android users, both indicators were tracked via App Usage – Manage/Track Usage version 5.12 & 5.14 App, which is similar to the interface on iOS. To gather the data from the apps, participants are required to screenshot their daily screen-time and screen checking from the apps and upload it to

Qualtrics (see Figure 1 for examples of screenshot). The data were then hand-coded and averaged across the 8 days to obtain an average level of objective screen time and screen-checking for each participant.

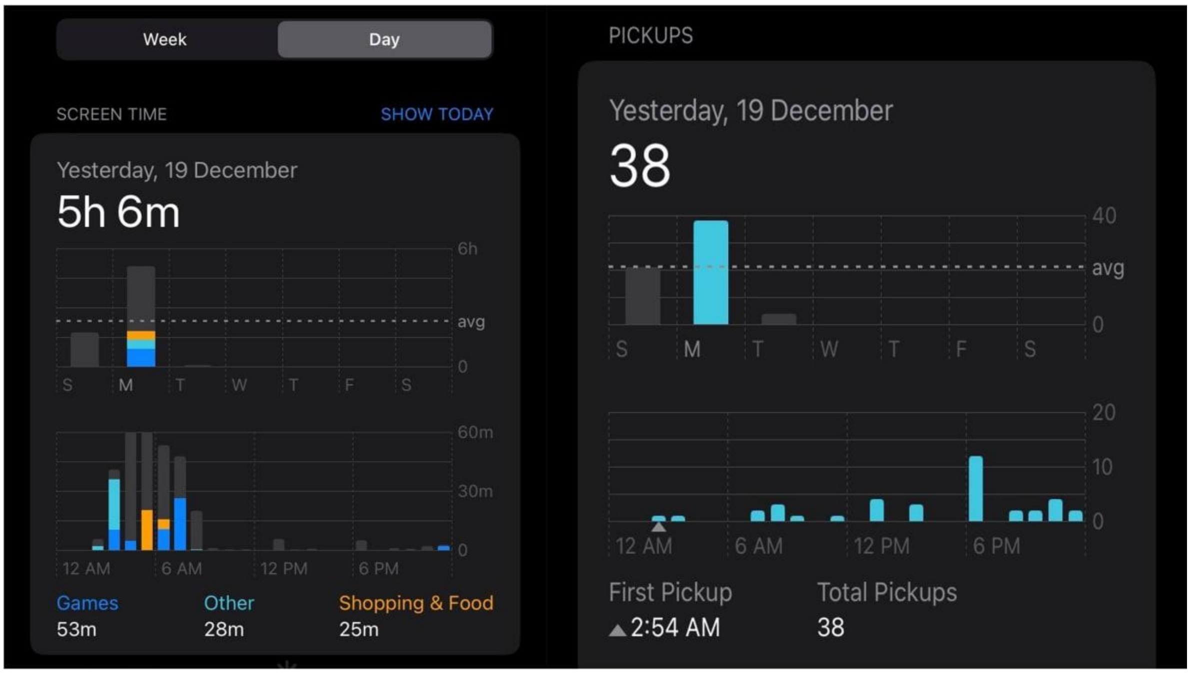

Figure 1. Samples of screenshots from the inbuilt iOS screen time application programming Interface

Working Memory Capacity

Operation Span Task. The operation span task adapted from Foster et al. (2015) was the first complex span task administered on E-prime version 3.0 (Psychology Software Tools, Pittsburgh, PA) to assess working memory capacity. In this task, participants were first instructed to solve a simple arithmetic problem, after which they were asked to memorize a target letter displayed on the screen. To calculate the response deadline on the distraction task (i.e., arithmetic problem), the task timed participants' reaction time while practicing the arithmetic problem during the practice trial. Participants were then required to respond within

2.5 standard deviations (SDs) of their average time response to each distraction item. This allowed the tasks to impose response deadline for distraction items in each task and reduce our participants' ability to rehearse the to-be-remembered target during the distraction tasks. The total number of to-be-remembered target letters (set size) varied from three to seven per set. Performance on the operation span task was calculated by computing the partial credit unit score (PCU; Conway et al., 2005). To calculate the PCU score, accuracy per trial (fraction of stimuli accurately remembered over the total number of stimuli shown) was first determined before computing the mean accuracy across all trials.

Rotation Span Task. The rotation span task adapted from Foster et al. (2015) was the second complex span task administered on E-prime to assess working memory capacity. In this task, participants first viewed a rotated letter and judged whether it was a laterally inverted version of the target letter when positioned vertically. Subsequently, they had to memorize the length and direction of an arrow displayed on the next screen, which was either long or short and pointing in one of the eight cardinal directions. Similar to the operation span task, the rotation span task also timed participants' reaction time while practicing the distraction task during the practice trial. Participants were then required to respond within 2.5 standard deviations (SDs) of their average time response to each distraction item (i.e., memorizing the length and direction of an arrow). The total number of to-be-remembered target arrows (set size) varied from two to five per set. Similarly, performance was indexed by the PCU score.

Symmetry Span Task. The symmetry span task adapted from Foster et al. (2015) was the third complex span task administered on E-prime to assess working memory capacity. In this task, participants were instructed to decide whether a displayed pattern was symmetrical along a central vertical line, before memorizing the position of a red square on a 4×4 grid presented on the next screen. The symmetry span task also timed participants' reaction time while practicing the distraction task during the practice trial. Participants were then required to respond within 2.5 standard deviations (SDs) of their average time response to each distraction item (i.e., deciding whether a displayed pattern was symmetrical). The total number of to-be-remembered target positions (set size) varied from two to five per set. Similarly, performance was indexed by the PCU score.

Inhibitory Control

Simon Task. The Simon task was the first inhibitory control task administered on Tatool Web (Von Bastian, Locher, & Ruflin, 2013). In this task, participants had to respond to the color of a circle as quickly and as accurately as possible by pressing either the left (for green) or right (for red) arrow key. The circle emerged on either the left or right side of the screen. During congruent trials, the position of the circle (distractor) was on the same side as the correct arrow key press (i.e., green circle on the left, or red circle on the right). During incongruent trials, the position of the circle (distractor) was on the opposite side of the correct arrow key press (i.e., green circle on the right, or red circle on the left). The current Simon task consisted of 12 practice trials, and a total of 200 actual trials with 75% congruent trials and 25% incongruent trials. The decision to use 75% congruent trials and 25% incongruent trials was motivated by findings that showed demands of inhibitory control to be higher with a decreasing proportion of incongruent trials (Logan & Zbrodoff, 1979). The exact same task administered on Tatool Web with similar proportion of trial conditions and task instruction has been shown to be successfully in generating Simon effect and widely used in studies examining individual differences in inhibitory control (Oschwald, Schättin, von Bastian, & Souza, 2018; Rey-Mermet et al., 2019; von Bastian, Souza & Gade, 2016).

Flanker Task. The Flanker task was the second inhibitory control task administered on Tatool Web (Von Bastian et al., 2013). In this task, participants viewed an array of seven characters (letters or symbols) displayed in the middle of the screen and were required to make a directional response based on the central letter. When the central letter was a vowel, participants had to press the left arrow key, and when it was a consonant, they had to press the right arrow key. During congruent trials, the distractors and target are of the same category (e.g., "EEEAEEE"), while during incongruent trials, the distractors and target are in different category (e.g., "TTTATTT"). During neutral trials, the adjacent letters were substituted with symbols (e.g., "###E###") that did not correspond to any arrow key presses. The current Flanker task consisted of 12 practice trials, and a total of 144 actual trials with equal number of congruent, incongruent, and neutral trials.

Stroop Task. The Stroop task was the third inhibitory control task administered on Tatool Web (Von Bastian et al., 2013). In this task, participants viewed a series of characters (non-numeric symbols or numbers between 1 and 4) displayed in the middle of the screen and pressed a number on the keypad that was equivalent to the total number of characters shown. For congruent trials, the total number of characters displayed corresponded to the indicated integer (e.g., "333"), whereas, for incongruent trials, the total number of characters displayed did not match the indicated integer (e.g., "444"). For neutral trials, non-numeric symbols were presented instead of integers (e.g., “###”). The current Stroop task consisted of 12 practice trials, and a total of 144 actual trials with equal number of congruent, incongruent, and neutral trials.

Task-Switching

Animacy-Size Switching Task. The animacy-size switching task was the first task-switching task administered on Tatool Web (Von Bastian et al., 2013). In each trial, participants saw a cue and a bivalent stimulus. The cue was either an animacy cue (an image of paw prints) or a size cue (an image of soccer balls) and was presented 150 ms before stimulus onset. The stimulus was either a small animal (e.g., ladybug), a large animal (e.g., elephant), a small inanimate object (e.g., paper clip), or a large inanimate object (e.g., park bench). Depending on the cue shown, participants classified the stimulus by its animacy (animate or inanimate) or size (larger or smaller than a soccer ball) by pressing the corresponding left (for animate or smaller than a soccer ball) or right (for inanimate or larger than a soccer ball) arrow key. The task consisted of four single-task blocks (i.e., only one cue) and one mixed-task block (i.e., a mix of two cues). The blocks were arranged in a sandwich-like design, displayed in the following order: single-task block (cue 1), single-task block (cue 2), mixed-task block (a mix of cues 1 and 2), single-task block (cue 2), single-task block (cue 1). There were 64 trials per single-task block and 129 trials for the mixed-task block. Half of the trials in the mixed-task blocks were *switch trials* in which participants viewed alternating cues across consecutive trials. The remaining half of the trials were *repeat trials*, where participants continuously saw the same cue as in the previous trial.

Color-Shape Switching Task. The color-shape switching task was the second task-switching task administered on Tatool Web (Von Bastian et al., 2013). In this task, participants viewed a bivalent stimulus and a cue before classifying the stimulus according to the cue type displayed. The cue was either a color cue (an image of a color gradient) or a shape cue (an image of a row of small black diamonds) and was presented 150 ms before stimulus onset. The color of the stimulus was either blue or green, and its shape was either pointed or circular. Depending on the cue shown, participants classified the stimulus by its color (blue or green) or shape (circular or pointed) by pressing the corresponding left (for blue or circular) or right (for green or pointed) arrow key. The task consisted of four single-task blocks (i.e., only one cue) and one mixed-task block (i.e., a mix of two cues), arranged in a sandwich-like design similar to the previous task. There were 64 trials per single-task block and 129 trials for the mixed-task block with an equal number of switch and repeat trials.

Magnitude-Parity Switching Task. The magnitude-parity switching task was the third task-switching task administered on Tatool Web (Von Bastian et al., 2013). Similar to the previous two tasks, participants viewed a bivalent stimulus and a cue before classifying the stimulus according to the cue type displayed. The cue was either a magnitude cue (a series of large blue circles and small yellow circles) or a parity cue (alternating rows of green and pink dashed lines) and was presented 150 ms before stimulus onset. The stimulus was a number between 1 and 9, excluding 5. Depending on the cue displayed, participants classified the stimulus by its magnitude (less than or greater than 5) or parity (even or odd) by pressing the corresponding left (for less than 5 or even) or right (for greater than 5 or odd) arrow key. As in the previous two tasks, the task consisted of four single-task blocks (i.e., only one cue) and one mixed-task block (i.e., a mix of two cues), arranged in a sandwich-like design. There were 64 trials per single-task block and 129 trials for the mixed-task block with an equal number of switch and repeat trials.

Procedure

All participants completed the study in two sessions. During the baseline session, participants provided informed consent, filled in their background information, measures of self-reported smartphone usage, and other questionnaires in a quiet setting. Over eight days between the baseline session and the executive functions session, a smartphone application recorded participants' screen time and frequency of screen-checking. Within 11 to 14 days from the baseline session, participants performed a series of executive function tasks for 90 minutes while sitting separately in open booths in a quiet computer laboratory. All participants completed the nine executive function tasks in the following sequence: (1) operation span task, (2) rotation span task, (3) symmetry span task, (4) Simon task, (5) Flanker task, (6) Stroop task, (7) animacy-size switching task, (8) color-shape switching task, and (9) magnitude-parity switching task. The order of the task administration was fixed for all participants to minimize any measurement error due to participant by order interaction (e.g., Miyake et al., 2000).

Analysis Plan

Following previous recommendations (Draheim, Hicks, & Engle, 2016; Hughes, Linck, Bowles, Koeth, & Bunting, 2014), a binning procedure was employed to index performance on each of the six tasks assessing inhibitory control and task-switching by combining speed and accuracy into a single comprehensive score. The binning procedure has been showed to improve the construct validity and reliability of executive functions tasks, as compared to pure latency or accuracy scores. Based on the procedure described by Draheim et al. (2016), we first trimmed accurate responses that were below 200 milliseconds. We also trimmed accurate responses that were 2.5 *SD* above or below an individual's mean reaction time for task-switching tasks. For inhibitory control tasks, we trimmed accurate responses that were 3 *SD* above or below an individual's mean reaction time. Subsequently, the mean reaction time on correct congruent trials (in inhibitory control tasks) or correct repeat trials (in task-switching tasks) was calculated for each participant. This score, representing participant's "baseline" reaction time, was then subtracted from the reaction time of each accurate incongruent trial (in inhibitory control tasks) or accurate switch trial (for task-switching tasks). The resulting values, referred to as *interference effects* for inhibitory control tasks or trial-based *switch costs* for task-switching tasks, indicate how quickly a participant responds accurately on each incongruent or switch trial compared to their "baseline" reaction time value. The interference effects or trial-based switch costs across all participants on all accurate incongruent or switch trials were rank-ordered and categorized into ten deciles. A bin value from 1 (fastest 10%) to 10 (slowest 10%) was assigned to each decile. Additionally, a bin value of 20 was assigned for each inaccurate incongruent or switch trial irrespective of response time. Lastly, the mean bin score across all incongruent or switch trials were computed to determine bin scores for each participant, with a lower bin score reflecting better performance.

After the data pre-processing, using a specified three-factor model of executive function (i.e., working memory capacity, inhibitory control, task-switching ability), latent variable analyses were conducted to statistically extract the common variance behind the same underlying latent construct. This enabled us to minimize the influence of measurement error in addition to non-executive function processes specific to each task. Hence, from a total of nine tasks—with three tasks per latent variable as described earlier—we estimated the three latent variables. PCU scores on complex span tasks (i.e., operation span, rotation span, symmetry span) were used to manifest working memory capacity, binned interference effects on the inhibitory control tasks (i.e., Simon task, Flanker task, and Stroop task) were used to manifest inhibitory control, and binned switch costs on the task-switching paradigms (i.e., animacy-size switching task, color-shape switching task, magnitude-parity switching task) were used to manifest task-switching ability. Each latent variable was allowed to correlate freely with the other two latent variables.

Thereafter, we ran separate structural models for each smartphone-related measure (i.e., self-reported problematic smartphone usage, self-reported normative smartphone usage, objective screen time, objective screen-checking) using structural equation modelling. Both unadjusted and adjusted structural models were estimated. In the adjusted model, we controlled for demographic covariates (i.e., age, sex, race, household income, subjective socioeconomic status). We used several fit indices to determine model fit; higher values of Bentler's comparative fit index (CFI) and the Tucker-Lewis index (TLI), as well as lower values of Akaike's information criterion (AIC), Bayesian information criterion (BIC), standardized root mean-squared residual (SRMR), and root mean square error of approximation (RMSEA), indicated a better fit. When judging model fit, we followed established cut-offs, whereby an excellent model fit would be indicated by CFI $\approx$ .95, TLI

≈ .95, and SRMR ≈ .08 (Hu & Bentler, 1999), as well as RMSEA < .06 (Browne & Cudeck, 1992).

Finally, to ensure the robustness of our results, acknowledging that our original binning procedure did not correct for error rate on congruent trials and may arbitrarily put a large weight on inaccurate trials, we conducted multiverse sensitivity analyses with with different binning and scoring methods to index performance on the inhibitory control and task-switching tasks. In total, we used three different variants of the original binning procedure, a simple difference score in reaction times, and an inverse efficiency scoring (Townsend & Ashby, 1983) as different indicators of participants' performance on inhibitory control and task switching. The second variant of our binning procedure (Binning Procedure 2) was similar to the original binning procedure except that inaccurate incongruent trials/inaccurate switch trials received a bin score of 11 instead of a bin score of 20. In the third variant of our binning procedure (Binning Procedure 3), a bin score of 20 was assigned to the number of incongruent-minus-congruent errors/switch-minus-repeat errors, which was added to the bin scores of the accurate incongruent/switch trials calculated with the original binning procedure, and the total was divided by the number of incongruent/switch trials. The fourth variant of our binning procedure (Binning Procedure 4) was similar to binning procedure 3, except that the number of incongruent-minus-congruent errors/switch-minus-repeat errors was instead scored with a bin score of 11. The inverse efficiency score (Townsend & Ashby, 1983) was calculated by subtracting the ratio of participants' mean reaction time on congruent/repeat trials to their mean accuracy level on congruent/repeat trials from the ratio of participants' mean reaction time on incongruent/switch trials to their mean accuracy level on incongruent/switch trials.

Statistical Power

We conducted series posteriori power analysis using the Shiny Apps (https://yilinandrewang.shinyapps.io/pwrSEM/) by Wang and Rhemtulla (2021). The parameter values were set to a regression coefficient of $\beta = .10$, .20, and .30 for the target effect. After 1000 simulations, with an alpha of .05 or less, the results suggest that with 260 participants, we only have .29 power for $\beta = .10$, .79 power for $\beta = .20$, and .98 power for $\beta = .30$.

Transparency and Openness

This study's design and its analysis plan were not pre-registered. All subject-aggregated data have been made publicly available on Researchbox (#330; https://researchbox.org/). All analyses were conducted in R version 3.6.3 (R Core Team, 2020) using lavaan version 0.6-9 (Rosseel, 2012) set to mimic Mplus (Muthén & Muthén, 2012) in all calculations. We used full-information maximum likelihood parameter estimation to handle missing data.

Results

Model Fit

Table 1 shows a summary of the sample's descriptive statistics. For our model fit, consistent with the three-factor model of executive functions hypothesized by Miyake et al. (2000), the fit of the current three-factor measurement model of executive functions was excellent, CFI = .98, TLI = .97, SRMR = .04, RMSEA = .04, and each manifest variable loaded significantly onto its corresponding latent variable (*p*s < .001). Of import, we found a significant positive correlation between the latent factors of inhibitory control and task-switching ($r = .51$, $p < .001$). However, different from Miyake et al., (2000), the latent factor of working memory capacity was not associated with inhibitory control ($r = .01$, $p = .914$) nor with task-switching ability ($r = -.11$, $p = .226$). Nevertheless, the model fits for our structural models with covariates were excellent. As shown in Table 2, both the unadjusted and adjusted structural models had near or excellent fits when examining each of the four smartphone-related variables as predictors of executive functions (CFIs > .96, TLIs > .95, SRMRs = .04, RMSEAs = .04).

Table 1

Descriptive Statistics of the Sample

	N	*M* (*SD*)	Range	Reliability [f]
Demographics				
Sex (% female)	260	74.23%		
Age	260	22.35 (1.71)	19–30	
Household income [a]	260	3.05 (1.46)	1–6	
Subjective socioeconomic status [b]	260	6.21 (1.38)	3–9	
Smartphone Usage Measures				
Problematic smartphone usage	260	3.30 (0.99)	1.00–5.90	.84
Mobile technology engagement	260	0.00 (0.66)	-1.76–1.78	
Average screen time (hours) [c]	259	5.80 (1.99)	0.61–11.80	
Average screen-checking [c]	259	125.54 (57.47)	0.12–321.50	
Executive functions [d]				
Operation span	258	.90 (.11)	.12–1.00	.654
Rotation span	246	.62 (.12)	.1–.80	.593
Symmetry span	259	.66 (.12)	.05–.80	.705
Simon task [e]	256	6.76 (1.47)	3.38–13.24	.773
Flanker task	256	6.40 (1.36)	2.99–16.96	.781
Stroop task	256	6.68 (1.19)	4.20–11.75	.736
Animacy-size task	255	6.65 (1.09)	4.06–9.53	.548
Color-shape task	254	6.71 (1.26)	4.23–12.11	.714
Magnitude-parity task	249	6.90 (1.55)	2.69–13.50	.841

Note. [a] A 6-point scale was used to determine monthly household income (1 = *less than $2,000*, 2 = *$2,000–$5,999*, 3 = *$6,000–$9,999*, 4 = *$10,000–$14,999*, 5 = $*15,000–$19,999*, 6 = *more than $20,000*). [b] We used a modified version of the ladder scale by Adler et al. (2000) to assess subjective socioeconomic status. [c] One participant did not submit data on average screen time and average screen-checking. [d] Technical faults and participant error resulted in some incomplete data. [e] One participant performed exceedingly poorly (i.e., 13% accuracy) on the Simon task, and hence we omitted data from that participant on that task. [f] Internal reliability for measures of smartphone usage were calculated using Cronbach's alpha, and internal reliability for measures of executive functions were calculated using split-half reliability with the Spearman-Brown correction.

Table 2

Summary of Model Fits

	df	χ^2	p_{χ^2}	AIC	BIC	SRMR	RMSEA	CFI	TLI
Measurement Model	24	31.99	.127	7158.28	7265.10	.04	.04	.98	.97
Structural Models									
Predictor: Self-Reported Problematic Smartphone Usage									
Unadjusted Model	30	37.74	.157	7153.47	7270.97	.04	.03	.98	.97
Unadjusted Path Fixed Model	32	46.15	.050	7157.88	7268.26	.05	.04	.97	.95
Adjusted Model	60	67.69	.231	7162.39	7333.30	.04	.02	.98	.97
Adjusted Path Fixed Model	62	73.66	.148	7164.36	7328.15	.04	.03	.97	.96
Predictor: Self-Reported Normative Smartphone Usage									
Unadjusted Model	30	34.50	.261	7156.99	7274.49	.04	.02	.99	.98
Unadjusted Path Fixed Model	32	37.58	.229	7156.07	7266.45	.04	.03	.99	.98
Adjusted Model	60	64.29	.329	7163.84	7334.75	.04	.02	.99	.99
Adjusted Path Fixed Model	62	67.03	.309	7162.58	7326.37	.04	.02	.99	.98
Predictor: Objective Screen Time									
Unadjusted Model	30	34.56	0.259	8249.95	8374.57	.04	.02	.99	.98
Unadjusted Path Fixed Model	32	40.46	.145	7121.74	7232.00	.05	.03	.98	.97

Adjusted Model	65	74.27	.202	11552.02	11801.26	.04	.02	.98	.97
Adjusted Path Fixed Model	67	77.67	.175	11551.42	11793.55	.04	.03	.98	.97
Predictor: Objective Screen-Checking									
Unadjusted Model	30	37.32	.168	9997.48	10122.11	.04	.03	.98	.97
Unadjusted Path Fixed Model	32	39.73	.163	7123.45	7233.71	.04	.03	.98	.97
Adjusted Model	65	81.08	.086	13298.42	13547.67	.04	.03	.96	.95
Adjusted Path Fixed Model	67	81.19	.114	13294.53	13536.66	.04	.03	.97	.95

Note. AIC = Akaike's information criterion; BIC = Bayesian information criterion; SRMR = standardized root mean-squared residual; RMSEA = root mean square error of approximation; CFI = Bentler's comparative fit index; TLI = Tucker-Lewis index. Lower values of AIC, BIC, SRMR, and RMSEA indicate better fit. Higher values of CFI and TLI indicate better fit. The unadjusted model includes the smartphone-related measures (i.e., self-reported problematic smartphone usage, self-reported normative smartphone usage, objective screen time, objective screen-checking), while the adjusted model additionally includes the covariates of age, sex, race, household income, and subjective socioeconomic status.

Self-Reported Normative Smartphone Usage

Next, we estimated structural models for self-reported normative smartphone usage as a predictor of the three latent variables of inhibitory control, task-switching, and working memory capacity. In the unadjusted model, self-reported normative smartphone usage was not a significant predictor of the latent factor of inhibitory control (β = -.07, z = -0.83, *p* = .406), task-switching (β = .08, z = 1.05, *p* = .291), and working memory capacity (β = .14, z = 1.87, *p* = .062). After controlling for demographics in the adjusted model, self-reported normative smartphone usage was still not a significant predictor of latent factor of inhibitory control (β = -.06, z = -0.81, *p* = .420) and task-switching (β = .05, z = 0.67, *p* = .505), but was a significant predictor of working memory capacity (β = .16, z = 2.05, *p* = .040), suggesting that that individuals with a self-reported normative smartphone usage displayed higher working memory capacity.

Objective Screen Time and Screen-Checking

Subsequently, we estimated structural models for objective screen time in predicting latent variables of executive functions. In the unadjusted model, we found that objective smartphone screen time was not associated with any latent factor of executive functions: inhibitory control (β = -.06, z = -0.75, *p* = .454), task-switching (β = .11, z = 1.51, *p* = .131), and working memory capacity (β = .13, z = 1.82, *p* = .069; see Figure 2). In the adjusted model, objective smartphone screen time was still not a significant predictor of any of latent factors of inhibitory control (β = -.07, z = -0.88, *p* = .381), task-switching (β = .09, z = 1.17, *p* = .242), and working memory capacity (β = .13, z = 1.74, *p* = .081).

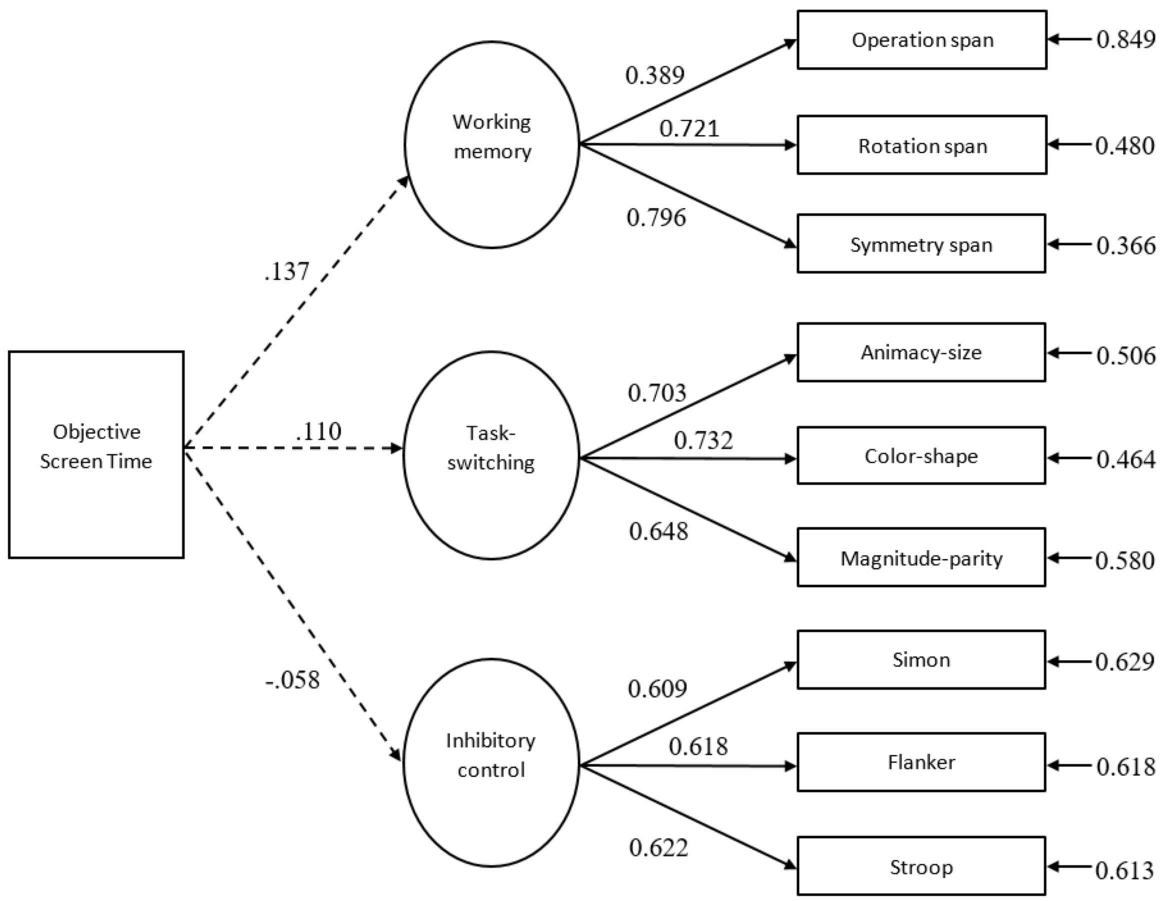

Figure 2. Structural Equation Model of the Three-Factor Executive Function Regressed Against Objective Screen Time in the Unadjusted Model. Circles represent latent variables while boxes represent manifest variables. Single-headed arrows on the right of the figure represent error terms. Dotted lines represent nonsignificant regression path (p > .05). Higher scores for both task-switching and inhibitory control reflect poorer task-switching and inhibitory control performance, respectively.

We also estimated structural models for objective screen-checking in predicting latent variables of executive functions. Similarly, in our unadjusted model, objective screen-checking was not associated with latent factor of inhibitory control (β = .02, z = 0.27, p = .785), task-switching (β = .07, z = 0.961, p = .337), and working memory capacity (β = .11, z = 1.43, p = .152). The null finding remained consistent in our adjusted model: inhibitory control (β = .03, z = 0.35, p = .730), task-switching (β = .04, z = 0.60, p = .558), and working memory capacity (β = .12, z = 1.54, p = .123).

Self-Reported Problematic Smartphone Usage

Lastly, structural models with problematic smartphone usage as a predictor were estimated (see Figure 3 for unadjusted model). In contrast to our previous findings, we found that problematic smartphone usage was positively associated with the latent factor of task-switching in both the unadjusted model (β = .20, z = 2.70, p = .007) and when demographic covariates were controlled for in the adjusted model (β = .16, z = 2.21, p = .027), suggesting that problematic smartphone usage was associated with deficits in task-switching. However, problematic smartphone usage was not significantly associated with inhibitory control in both the unadjusted model (β = -.05, z = -0.64, p = .524) and the adjusted model (β = -.05, z = -0.68, p = .500). Similarly, problematic smartphone usage was not a significant predictor of working memory capacity in both the unadjusted model (β = .03, z = 0.46, p = .645) and the adjusted model (β = .06, z = 0.77, p = .440).

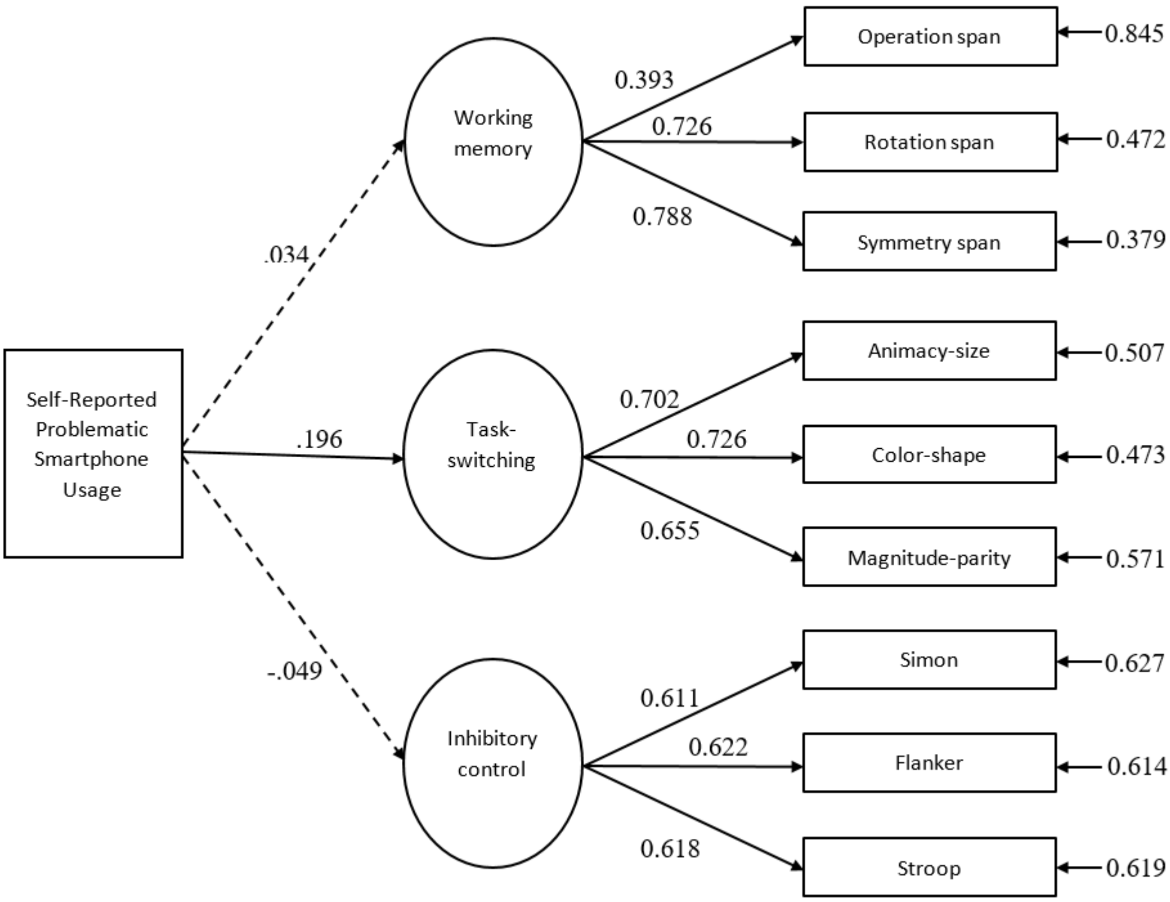

Figure 3. Structural Equation Model of the Three-Factor Executive Function Regressed Against Self-Reported Problematic Smartphone Usage in the Unadjusted Model. Circles represent latent variables while boxes represent manifest variables. Single-headed arrows on the right of the figure represent error terms. Dotted lines represent nonsignificant regression path (p > .05). Higher scores for both task-switching and inhibitory control reflect poorer task-switching and inhibitory control performance, respectively.

Sensitivity Analyses

Different binning procedures and scoring methods were used to determine whether the associations between different indicators of smartphone use and executive functions remained stable across different binning procedures and scoring methods. (Table 3). All of the analyses were conducted using structural equation modeling with latent factors of executive functions, except for the simple difference score in RT and inverse efficiency score due to convergence failure in the measurement models. In this case, we conducted the sensitivity analyses on inverse efficiency score and reaction time difference by averaging the performance of tasks in each factor of executive functions and employing ordinary linear regression.Generally, results remained consistent across the different scoring procedures. However, the relationship between task-switching and self-reported problematic smartphone use remained significant only in the unadjusted model for binning procedure 2, inverse efficiency score, and reaction time difference score, but was not significant for the other binning procedures. Furthermore, there was a significant relationship between task switching and self-reported normative smartphone use in the unadjusted model for binning procedure 3, binning procedure 4, inverse efficiency score, and reaction time difference score, but this relationship was not significant for the original binning procedure and binning procedure 2 ((|β|s=[.05, .14]).

Table 3

Sensitivity Analyses with Variety of Measurement Approaches

Variation in analysis	Self-reported Normative Smartphone Usage				Objective Screen Time				Objective Screen Checking				Self-Reported Problematic Smartphone Usage			
	Unadjusted		Adjusted		Unadjusted		Adjusted		Unadjusted		Adjusted		Unadjusted		Adjusted	
	β	*p*	β	*p*	β	*p*	β	*p*	β	*p*	β	*p*	β	*p*	β	*p*
Original Results (for comparison)																
Task Switching	.08	.291	.05	.505	.11	.131	.09	.242	.07	.337	.04	.558	.20	**.007**	.16	**.027**
Inhibitory Control	-.07	.406	-.06	.420	-.06	.454	-.07	.381	.02	.785	.03	.730	-.05	.524	-.05	.500
Binning Procedure 2																
Task Switching	.14	.069	.11	.154	.12	.103	.10	.189	.09	.237	.07	.336	.18	**.017**	.14	.066
Inhibitory Control	-.10	.269	-.09	.311	-.08	.367	-.08	.326	-.01	.920	.004	.959	-.10	.251	-.11	.219
Binning Procedure 3																
Task Switching	.18	**.036**	.16	.050	.07	.330	.06	.433	.09	.246	.08	.289	-.08	.287	-.10	.183
Inhibitory Control	-.01	.883	-.02	.824	-.04	.617	-.07	.466	.10	.251	.10	.284	-.01	.925	-.01	.903
Binning Procedure 4																

Task Switching	.14	**.037**	.15	**.046**	.05	.475	.04	.552	.09	.208	.09	.214	-.07	.292	-.09	.200
Inhibitory Control	.16	.600	-.05	.599	-.08	.363	-.11	.261	.02	.808	.04	.709	-.07	.489	-.07	.446
Inverse Efficiency Score																
Task Switching	.17	**.006**	.15	**.014**	.06	.340	.05	.432	.05	.419	.06	.379	.15	**.019**	.12	.054
Inhibitory Control	.01	.826	.01	.913	-.03	.586	-.05	.480	-.01	.868	-.01	.867	.02	.778	-.001	.994
Reaction Time Difference Score																
Task Switching	.16	**.011**	.14	**.025**	.04	.481	.04	.560	.03	.613	.04	.535	.15	**.019**	.13	.053
Inhibitory Control	.02	.761	.02	.756	.03	.667	.02	.765	.04	.563	.05	.403	.02	.720	.01	.865

Discussion

Smartphone adoption and daily usage are growing rapidly around the world as its technology continues to bring more functionality and convenience to human lives (O’dea, 2021). Due to the ubiquity of smartphones, the notion that using smartphones could be harmful and detrimental to humans’ cognition, particularly executive functions, has gained traction in popular media (Merzenich, 2013; Williams, 2019; for a review, see Wilmer et al., 2017). However, there is a lack of strong scientific support for the negative relationship between smartphone usage and cognitive functions. Given the widespread moral panic over banning smartphones (Rao & Lingam, 2021; Walsh, 2020), it is important to develop a better understanding of the relationship between smartphone usage and cognitive functions and its boundary conditions. Therefore, the current study was conducted to examine the relationship between smartphone usage and the latent factors of executive functioning, namely inhibitory control, task-switching, and working memory. Expanding on previous studies, we made several methodological advancements, such as distinguishing normative smartphone use from problematic smartphone use, employing objective data-logged measurement of smartphone usage, and utilizing latent variable approaches to examine executive functions.

Overall, we found that normative smartphone usage was not associated with deficits in executive functions. When measured objectively, screen time and frequency of screen-checking did not significantly predict the latent factors of inhibitory control, task-switching, and working memory capacity. The findings are in contrast to the assumptions that extensive usage of smartphones may have long-term implications to our cognitive functions due to the distracting nature of smartphones (Fabio et al., 2022; Merzenich, 2013; Williams, 2019). Instead, the findings also suggest that short-term impairment in executive functions by the distraction of smartphone found in the existing studies (e.g., Thornton et al., 2014; Ward et al., 2017) may not translate to long-term adverse effect on cognitive functions. Thus, the mechanism underlying the impairment of cognitive functions due to smartphone found in the previous study is likely to be situational-specific and temporary. Moreover, the lack of evidence supporting the long-term negative implications of smartphone on cognitive functions are also consistent with recent findings that failed to find far-transfer effect in computerized working memory training programs and various other experiential factors (e.g., chess, music, video game) (Melby-Lervåg, Redick, & Hulme, 2016; Redick et al., 2013; Sala & Gobet, 2017; Unsworth et al., 2015; Wiradhany, van Vugt, & Nieuwenstein, 2020).

Interestingly, we found that self-reported normative smartphone usage, measured by the Mobile Technology Engagement Scale (Wilmer & Chien, 2016), significantly predicted enhanced working memory capacity, but not inhibitory control and task-switching. A possible explanation for this positive finding in relation to self-reported normative smartphone usage and working memory capacity could be that the Mobile Technology Engagement Scale focuses more on evaluating smartphone-based social media use (Wilmer & Chien, 2016). Recent studies have shown preliminary evidence that social media usage in young and midlife adults is associated with enhanced executive functioning via higher perceived social support and sense of control (Alloway & Alloway, 2012; Khoo & Yang, 2020). Thus, it is plausible that specific types of smartphone usage, such as social media use, are positively associated with executive functioning due to their adaptive functions. These findings highlight the importance of distinguishing between the purpose of smartphone usage—even for objective measures of smartphone usage—when examining its association with executive functions. Nevertheless, the positive association between self-reported normative smartphone usage and working memory capacity should be interpreted with caution given the small effect size and barely significant *p* value ($p = .04$) in the adjusted model.

In addition, we found that self-reported problematic smartphone usage was associated with deficits in the latent factor of task-switching. One could argue that these findings may suggest that problematic smartphone usage—such as excessive smartphone usage, lack of impulse control, and smartphone-related daily life interference—has negative implications for cognitive functions. However, it is important to note that the negative association in our structural equation model was not replicated in objective screen time and screen-checking, which could instead capture the construct of excessive smartphone usage more accurately (Hodes & Thomas, 2021; Parry et al., 2021; Shaw et al., 2020). Thus, it is also plausible to argue an alternative view that the negative association between self-reported problematic smartphone usage and executive functions that was observed in the current study could simply be driven by pre-existing individual differences in impulse control and cognitive failure. Rather than deficits in executive functions being the consequence of problematic smartphone use, it is more plausible that those with deficits in executive functions are more likely to have an unhealthy reliance on and uncontrolled usage of smartphones, driven by its rewarding and pleasurable experiences for users (Eyal, 2014; Hartanto, Quek, Tng, & Yong, 2021; Srivastava, 2005).

The results of our multiverse sensitivity analyses were also noteworthy. While most of our null associations in our original analyses remained robust, the statistical significance of some of the associations changed across different scoring procedures, such as those in the association between self-reported normative smartphone usage and task-switching as well as between problematic smartphone usage and task-switching. These findings from our multiverse sensitivity analyses as a whole suggest that slight variations of the analysis method may influence the associations between indicators of smartphone use and executive functions. This could be driven by the perspective that executive functions may not be a robust individual difference measure (Hedge et al., 2018; Rey-Mermet, Gade, & Oberauer, 2018; Rouder & Haaf, 2019). Therefore, we encourage the adoption of multiverse sensitivity analyses in future studies on individual differences in executive functions to ensure the robustness of the results.

Despite the methodological advances of the current study in relation to the latent variable approach and the use of objective data-logged measurement of smartphone usage, there were several limitations of the current study that should be acknowledged. First, the correlational nature of the current study limits our interpretation of the directionality in the relationship between smartphone usage and executive functions. As discussed, while problematic smartphone usage may impair executive functions, it is also highly plausible that individuals with deficits in executive functions are more vulnerable to problematic smartphone usage. Thus, future studies should consider employing longitudinal designs to ascertain the directionality of the relationship. Second, based on the recent findings and reviews (Hedge et al., 2018; Rey-Mermet, Gade, & Oberauer, 2018; Rouder & Haaf, 2019), it is noteworthy that executive function tasks, especially inhibitory control tasks, has been criticized as they may not be robust individual difference measures due to their low intraclass correlation coefficients (Hedge et al., 2018), exploratory power (Rey-Mermet et al., 2019), and correlation across tasks (Draheim et al., 2021; Rouder & Haaf, 2019). Thus, it is important to acknowledge that our results could be affected by the less-than-ideal validity and reliability of executive functions in general. Nevertheless, the binning procedure used in the current study has been shown to alleviate some of the concerns related to the psychometric properties of the attention control tasks (Draheim et al., 2016 & Hughes et al., 2014). Third, we decided to fix the order of the task administration for all participants to minimize any measurement error due to participant by order interaction (e.g., Friedman & Miyake, 2012). However, fixing the order of the task administration without alternating measures of each construct may also introduce potential confounds with practice or fatigue effect that is associated with the testing environment. Fourth, neither inhibitory control nor task-switching correlated with working memory capacity in our measurement models, which may suggest that the binning scores did not adequately capture the inhibition or switching constructs. the lack of latent correlations in working memory capacity could be partly due to confounds introduced by fixing the order of the task administration. Sixth, although our current sample was larger than the recommended size of 150 for latent variable analysis of latent factors with three or more indicators (Gerbing & Anderson, 1985; Holbert & Stephenson, 2002), our posterior power analysis showed that our sample size may not be large enough to have statistical power to reliably detect small effect size. This may also increase the possibility of spurious findings in our analysis (Loken & Gelman, 2017). Lastly, the generalizability of our findings is limited given that the current investigation is solely based on a younger Singaporean sample. To ensure generalizability, future studies should attempt to replicate the current findings with samples from other populations, such as older adults and smartphone users from developing countries.

Taken together, contrary to the claims by popular media, we did not find strong evidence of inherent harms in daily smartphone usage on cognitive functions. In fact, our data may suggest that the use of smartphone technology in moderation is safe and might be associated with higher working memory capacity. Future study should scrutinize further the link between problematic smartphone usage and task-switching to ascertain its replicability as well as potential reverse causation.

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