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Wei Xing TOH
Singapore Management University, weixing.toh.2017@phdps.smu.edu.sg

Wee Qin NG
Singapore Management University, wq.ng.2019@phdps.smu.edu.sg

Hwajin YANG
Singapore Management University, hjyang@smu.edu.sg

Sujin YANG
Ewha Womans University

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Disentangling the effects of smartphone screen time, checking frequency, and problematic use on executive function: A structural equation modelling analysis

Wei Xing Toh[1] · Wee Qin Ng[1] · Hwajin Yang[1] · Sujin Yang[2]

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Abstract

The pervasiveness of smartphone engagement among young adults has attracted growing interest regarding its impact on cognitive processes. However, research on the relation between smartphone use and executive function (EF)—a set of adaptive, goal-directed control processes—remains inconclusive due to imprecise estimation of EF dimensions and inconsistent operationalisation of smartphone use in past studies. Therefore, we examined how two indices of smartphone use—screen time and checking frequency—would predict EF (common EF, shifting-specific-, and working-memory-specific components), using a latent-variable approach based on a comprehensive battery of EF tasks. We also examined the moderating role of problematic smartphone use in the link between smartphone use and EF components. We found that screen time positively predicted working-memory-specific and shifting-specific abilities, whereas frequent checking was associated with enhanced shifting-specific, but poorer common EF, abilities. Importantly, problematic smartphone use moderated the relation between checking frequency and common EF. Overall, our findings demonstrate that different indices of smartphone use asymmetrically predict EF facets, thereby highlighting the construct distinctiveness of the various markers of smartphone engagement. Our findings imply that checking frequency and problematic use, rather than screen time, are the most promising targets for interventions that aim to circumvent cognitive impairments by curtailing smartphone use, especially in educational settings.

Keywords Smartphone use · Problematic smartphone use · Executive function · Smartphone checking behaviour

With more than 90% of young adults owning a smartphone (Pew Research Center, 2019), the ubiquity of smartphone use among young adults has attracted a surge of interest from researchers. In particular, prior research has focused on the impact of smartphone use on executive function (EF), a group of core cognitive control processes—inhibition, shifting, and working memory—that is crucial in regulating goal-directed behaviours (Miyake et al., 2000). Mixed findings, however, have been reported (e.g., Chen et al., 2016; Pluck et al., 2020), which could be attributed to methodological limitations, such as the task-impurity issue in EF tasks and ill-defined constructs of smartphone use. To resolve these issues, we sought to examine how the various indicators of smartphone use (i.e., self-reported daily screen time and frequency of phone checking) could be related to the multifaceted aspects of EF using a latent-variable approach. In view of the empirical importance of problematic smartphone use (e.g., Ward et al., 2017), we also investigated its role as a moderator in the association between smartphone use and EF.

✉ Wei Xing Toh
weixing.toh.2017@phdps.smu.edu.sg

✉ Hwajin Yang
hjyang@smu.edu.sg

[1] School of Social Sciences, Singapore Management University, Level 4, 90 Stamford Rd, Singapore 178903, Singapore

[2] Department of Psychology, Ewha Womans University, Seoul, South Korea

Smartphone Use and Executive Function

Executive Function

EF has been theorised to comprise three interrelated, but separable, cognitive processes (Miyake et al., 2000): (a) inhibition, which is the ability to suppress irrelevant stimuli; (b) shifting, which is the ability to switch back and forth between different task sets; and (c) working memory, which refers to the ability to retain and manipulate information. However, in

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recent theories (i.e., the nested factor model), common EF—the ability to sustain task goals to guide ongoing processing—has been proposed as a unitary factor that represents the shared variance among the three EF processes. Further, working-memory-specific (i.e., the gating of information in one's mind) and shifting-specific (i.e., flexible switching between different tasks) factors are proposed to account for the remaining variance in working memory and shifting tasks, respectively, after common variance has been extracted (Miyake & Friedman, 2012). Moreover, the inhibition-specific factor perfectly correlates with the common EF factor, thereby obviating the need for the inhibition-specific factor (Banich & Depue, 2015; Miyake & Friedman, 2012). Corroborating this notion, Dosenbach et al.'s (2008) dual-networks model of top-down control proposes that the fronto-parietal network enables the maintenance of task-relevant information in a readily accessible form to adjust control rapidly (i.e., shifting-specific), whereas the cingulo-opercular network stably maintains task sets (i.e., common EF). Together, these systems implement top-down control, enabling flexible and highly stable human behaviour. Despite the theoretical and empirical importance of the revised EF framework (Friedman & Miyake, 2017), prior research has primarily focused on the relation of smartphone use to either single facets of EF or non-EF processes (e.g., attention, memory, delay of gratification, and everyday cognitive functioning; for details, see Wilmer et al., 2017). Hence, our study aimed to extend the growing body of smartphone research by examining the links between smartphone use and the various components of the nested-factor EF model (i.e., common EF, working-memory- and shifting-specific factors). In the next section, we review prior studies that have examined the association between smartphone use and each aspect of EF.

Smartphone Use and Inhibition

Smartphones serve as an attractive source of distraction that draws attention from the focal task. Thus, it is plausible that excessive smartphone use adversely affects the inhibition of impulsive thoughts or actions that is essential for the regulation of behaviours in line with task goals (Miyake et al., 2000). For instance, it has been shown that prolonged and heavy use of smartphones is concomitant with poorer impulse control and inattention problems (Hadar et al., 2017), which ultimately undermines attentional efficiency and effectiveness. Similarly, Chen et al. (2016) demonstrated that problematic smartphone use predicted poorer inhibition on a modified go/no-go task at the electrophysiological level. Further, smartphone alerts and notifications have been shown to increase distractibility and generate task-irrelevant thoughts, and therefore interrupt and impair attentional focus on the primary task (Oulasvirta et al., 2011; Stothart et al., 2015). In contrast, other studies found no relation between smartphone use and inhibition. For instance, Chen et al. (2016) and Gao et al. (2020) found that problematic smartphone users did not show diminished performance on inhibition tasks (i.e., modified go/no-go). Similarly, a longitudinal study reported no significant differences between heavy and new smartphone users on the stop-signal task (Hadar et al., 2017). Taken together, the findings suggest mixed evidence on the impact of excessive smartphone use on inhibition.

Further, there is a growing consensus that successful performance on inhibition tasks is predominantly driven by the general goal-management abilities representative of common EF (Friedman & Miyake, 2017). Notably, neuroimaging evidence has shown that brain regions (e.g., right inferior frontal gyrus) previously thought to be responsible for inhibition may instead be more relevant to general goal-management (i.e., common EF) abilities (Banich & Depue, 2015), which underscores the centrality of common EF in explaining EF operations. Hence, previously reported findings based on inhibition measures in the smartphone and EF literature may be more reflective of the link between common EF and smartphone use.

Smartphone Use and Shifting

Relatively few studies have examined the relation between smartphone use and the shifting aspect of EF. On the one hand, some studies suggest a positive association between smartphone use and shifting. Because smartphone use often involves simultaneous engagement in multiple smartphone apps (e.g., listening to music while scrolling social media), shifting between different apps is required to complete intended tasks. Consistently, the literature on media multitasking suggests that extensive switching between different media applications entails proficient shifting operations, such as the efficient adaptation to new tasks and the inhibition of previous, no-longer-relevant tasks (Alzahabi & Becker, 2013). On the other hand, it is possible that frequent multitasking on smartphones interrupts the cognitive processes that suppress the activation of irrelevant task sets and, as a result, hampers the ability to effectively switch between tasks. In this vein, previous studies provide evidence that heavy media multitaskers are less effective in task switching (Ophir et al., 2009). Hence, the relation between smartphone use and shifting remains inconclusive and requires more in-depth investigation.

Smartphone Use and Working Memory

Smartphone use entails frequent consumption and management of multiple media sources, which may impair working memory capacity (Uncapher et al., 2016). Specifically, frequent multitasking may broaden attentional scope, which increases the likelihood of task-irrelevant information competing with task-relevant information. This, in turn, impairs the processing and maintenance of goal-relevant information within working memory (Uncapher et al., 2016). In line with this notion, Abramson et al. (2009) found that greater mobile phone use, in terms of messaging and calls, was associated with poorer working memory performance on the *n*-back task. However, this finding should be interpreted with caution, since it may not accurately reflect smartphone use in today's context.

Alternatively, smartphone engagement may be associated with better working memory. Considering that smartphones allow access to multiple sources of content, their use necessarily involves interruptions in the form of messages, notifications, or updated content from other applications (e.g., real-time news and social media feed refreshing; Deng et al., 2018). Accordingly, it has been suggested that interruptions from other smartphone applications require individuals to hold current information in mind before they resume the interrupted application and update new information regularly (Leiva et al., 2012). Further, Alloway and Alloway (2012) found that checking friends' status updates on Facebook, which encourages information storage (e.g., individual profiles) while frequently discarding irrelevant information (e.g., friends' previous status), predicted better working memory capacity. Taken together, these conflicting findings show that the relation between smartphone use and working memory warrants further investigation.

Limitations of Previous Studies

Notwithstanding the surge in research on the relation between smartphones and EF, previous studies have several limitations. First, it is plausible that the inconsistent findings may be due to inadequate operationalisation of smartphone use. Although smartphone engagement has been largely indexed by time spent on smartphones in past studies (e.g., Gao et al., 2020; Hadar et al., 2017), screen time may not precisely capture the downsides of smartphone use. Drawing on the unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003), individuals who perceive the smartphone as a useful tool that increases productivity (i.e., performance expectancy) may frequently use smartphones for constructive purposes (e.g., work). Therefore, smartphone screen time may not necessarily reflect problematic smartphone use (e.g., dependence, withdrawal symptoms, and daily-life disturbances; Pluck et al., 2020). Another crucial aspect of smartphone use that has received relatively less attention is the frequency of checking (Wilcockson et al., 2018). Studies have shown that checking frequency drives overall smartphone use (Oulasvirta et al., 2011) but is not significantly associated with total screen time, which suggests that these two indices may tap different aspects of smartphone use and yield different cognitive outcomes. Therefore, it is crucial that we consider not only screen time but also the frequency of smartphone checking as separate behavioural measures of smartphone use.

Second, there is a lack of understanding of how problematic smartphone-use tendencies would modulate the relations between smartphone use and EF. To illustrate, given the widespread reliance on smartphones to accomplish various day-to-day tasks, high levels of smartphone screen time or checking frequency may not inevitably signify problematic smartphone use. Indeed, some studies have shown that self-reported indices of smartphone use (e.g., screen time and checking frequency) are not associated with problematic smartphone use (Andrews et al., 2015), although individuals who demonstrate problematic smartphone behaviours may have increased screen time and checking behaviours (Gökçearslan et al., 2016). Further, past work has demonstrated that individuals with problematic tendencies may suffer greater cognitive costs from smartphone use. For instance, Hartanto and Yang (2016) showed that the negative effect of smartphone separation on inhibition was more pronounced in problematic smartphone users. Similarly, Ward et al. (2017) found that individuals with higher levels of problematic smartphone use demonstrated poorer working memory performance, due to the mere presence of their smartphones. Despite these findings, previous studies have only loosely distinguished problematic smartphone use from nonproblematic forms of smartphone use (Pluck et al., 2020). Therefore, it remains unclear whether the cognitive consequences of smartphone use may be contingent on problematic smartphone tendencies.

Third, considering that most EF tasks are not process-pure, as they assess not only EF-specific abilities (e.g., inhibition) but also non-EF abilities (e.g., verbal ability), inconsistent findings in the literature can be attributed to the task-impurity issue that has plagued a wide range of EF tasks. Further, since the majority of previous studies have relied on a single task to measure EF, it is difficult to isolate the EF components of interest (Miyake & Friedman, 2012). Specifically, with the use of a single EF measure, non-EF abilities may obscure the true relation between smartphone use and EF or spuriously drive the significant relation of smartphones to EF. Accordingly, further work is needed to more accurately estimate the construct-relevant components of EF tasks and how they are associated with the various indicators of smartphone engagement.

The Present Study

Considering the limitations of previous studies, we sought to distinguish between specific aspects of smartphone engagement (screen time and checking frequency) and examine their relations to common EF, working-memory-specific, and shifting-specific factors. Further, to resolve inconsistencies in the literature, we aimed to shed light on the moderating role of problematic smartphone use in the links between smartphone use and different EF facets. Moreover, to address the task-impurity issues inherent to EF measures, we used a structural equation approach to model latent variables of EF based on a comprehensive battery of EF tasks.

Specifically, we predicted that smartphone checking frequency may be inversely related to certain components of EF. Frequent checking, which signals a preoccupation with one's smartphone and interferes with long-term goals through goal-irrelevant thoughts (Oulasvirta et al., 2011; Wilcockson et al., 2018), likely impedes common EF, which is essential for sustaining attention for ongoing tasks. However, frequent smartphone checking may be positively associated with the shifting aspect of EF, since it implicates persistent switching between non-smartphone and smartphone-related activities.

In contrast, screen time may not be linked to impaired common EF. Specifically, given that smartphone engagement entails efficient switching between multiple applications (e.g., Alzahabi & Becker, 2013), greater screen time may be concomitant with better shifting. Similarly, we predicted that smartphone screen time would be positively related to working memory, since attending to disruptions from other apps requires users to maintain and update information whenever they resume the interrupted task (Alloway & Alloway, 2012; Leiva et al., 2012).

Additionally, in light of past findings that the negative effects of smartphone engagement on EF are magnified with increasing levels of problematic smartphone use (Hartanto & Yang, 2016; Ward et al., 2017), we hypothesised that the cognitive costs of smartphone use would be moderated by problematic tendencies. In particular, the negative impact of smartphone checking frequency on EF would be more pronounced for individuals with higher levels of problematic smartphone tendencies.

Method

Participants

One hundred and seventy undergraduate students ages 18–28 (M_{age} = 21.68 years, SD = 2.03; 66.3% female) were recruited from a local university over two academic semesters without specific inclusion or exclusion criteria and received either course credit or a monetary reward (S$30). The study was approved by the university's institutional review board, and informed consent was obtained from all participants prior to the study.

An a priori power analysis indicated that a minimum sample size of 137 was required to detect a medium effect size of .30 at 80% power (Soper, 2020) for a structural equation model comprising four latent variables and 20 manifest variables (see Results). Since the dataset for this study is part of a larger project, we analysed only the core variables of interest along with relevant demographic variables (see Table 1 for descriptive statistics).

Measures

Smartphone Use

Participants' smartphone use was assessed with respect to daily screen time (in hours) and checking frequency (in times), in line with past research that has examined smartphone use and cognitive abilities (e.g., analytical thinking, working memory; Alloway & Alloway, 2012; Barr et al., 2015). Using sliding scales, participants were asked to estimate how many hours they use their smartphones per day (from 0 to 24 h) and how many times they check their smartphones per day (from 0 to 200 times). Higher scores on these items denote greater smartphone use and frequent smartphone checking per day.

Problematic Smartphone Use

To assess the extent of participants' problematic smartphone use, we used the smartphone addiction scale, which is well established and widely used in relation to various outcomes (Kwon et al., 2013; Samaha & Hawi, 2016). Participants responded to 10 items (e.g., "I am having a hard time concentrating in class, while doing assignments, or while working due to smartphone use") using a 6-point scale (1 = *strongly disagree*, 6 = *strongly agree*). Scores are summed to yield a total score ranging from 10 to 60, with higher scores reflecting greater levels of problematic smartphone use.

Inhibition

We employed three inhibition tasks to assess the ability to suppress automatic prepotent responses (see Fig. 1; Friedman & Miyake, 2017).

Antisaccade. To assess the ability to resist attentional interference by the distracting cue, we used the antisaccade task adapted from Unsworth and McMillan (2014). Participants were directed to indicate, as fast and accurately as possible, the target stimulus (B, P, or R) that was flashed very briefly on one side of the screen, while ignoring a distracting cue ("=") that appeared on the other side of the screen; note that the distractor and the target letter always appeared on opposite sides of the screen. In each trial, a fixation point first appeared on the screen for a varying duration (from 200 ms to 2200 ms with 400 ms intervals), and the distracting cue was then shown to either the left or right of the fixation (11.33° of visual angle) for 100 ms. Thereafter, a blank screen appeared for 50 ms and was followed by the second appearance of the distracting cue for 100 ms, such that the distracting cue appeared to be flashing, and thus attracted more attention. Next, a 50-ms blank screen followed and the target stimulus was shown for 150 ms. It was masked by the letter H (50 ms) and then by the number 8 until a response was submitted. We administered

Table 1 Descriptive Statistics of Predictors, Covariates, and Criterion Variables

	M	*SD*	Min	Max	Skewness	Kurtosis	Reliability[a]
Predictors[b]							
Smartphone screen time	5.77	2.84	1.00	17.00	1.24	1.93	–
Smartphone checking	44.84	31.49	6.00	200.00	2.23	6.95	–
Problematic smartphone use	29.30	7.91	10.00	50.00	0.29	−0.08	.81
Criterion							
Executive function (EF)[c]							
Working memory[d]							
Operation span	0.85	0.15	0.02	1.00	−2.23	6.92	.76
Rotation span	0.68	0.19	0.07	1.00	−0.82	0.60	.73
Symmetry span	0.78	0.17	0.00	1.00	−1.56	3.47	.66
Inhibition							
Antisaccade[d]	0.73	0.17	0.26	1.00	−0.76	−0.29	.93
Go/no-go[d]	0.48	0.19	0.01	0.91	−0.18	−0.56	.93
Stroop[e]	14.18	1.91	2.29	17.19	−2.55	11.00	.79
Shifting							
Colour-shape[e]	14.20	1.90	3.24	17.19	−2.68	12.10	.80
Animacy-locomotion[e]	13.94	2.00	4.17	17.32	−1.88	5.56	.89
Magnitude-parity[e]	13.43	2.08	3.39	17.24	−1.35	3.38	.86
Covariates							
Gender (% female)	68.2	–	–	–	–	–	–
Household income[f]	4.22	2.38	1.00	9.00	0.54	−0.67	–
Fluid intelligence[d]	6.41	1.92	0.00	9.00	−0.76	0.21	.67
Extraversion[g]	2.82	0.94	1.00	4.75	0.14	−0.84	.84
Neuroticism[g]	3.06	0.83	1.00	5.00	−0.02	−0.11	.74

Note. [a] Reliability estimates were calculated using Spearman-Brown adjusted split-half correlations for Stroop, colour-shape, animacy-locomotion, and magnitude-parity tasks. For all other measures, reliability estimates were computed based on Cronbach's alpha.

[b] Smartphone screen time and smartphone checking were coded as number of hours and times per day, respectively. Problematic smartphone use was calculated using the total score on the smartphone addiction scale (Kwon et al., 2013).

[c] As a result of administrative and technical errors, data were missing for the following EF tasks: antisaccade ($n = 1$); go/no-go ($n = 1$); operation span ($n = 1$); symmetry span ($n = 1$); Stroop ($n = 4$); animacy-locomotion ($n = 1$); and magnitude-parity ($n = 2$).

[d] Accuracy scores were measured as the proportion of correct responses (i.e., operation-span, symmetry-span, rotation-span, antisaccade, and go/no-go tasks) and total number of correct responses (i.e., fluid intelligence).

[e] For the Stroop, colour-shape, animacy-locomotion, and magnitude-parity tasks, average bin scores were reverse-coded such that higher values denote better performance.

[f] Household income (monthly) was used as an index of socioeconomic status (1 = *$2500*, 9 = *$20,000*).

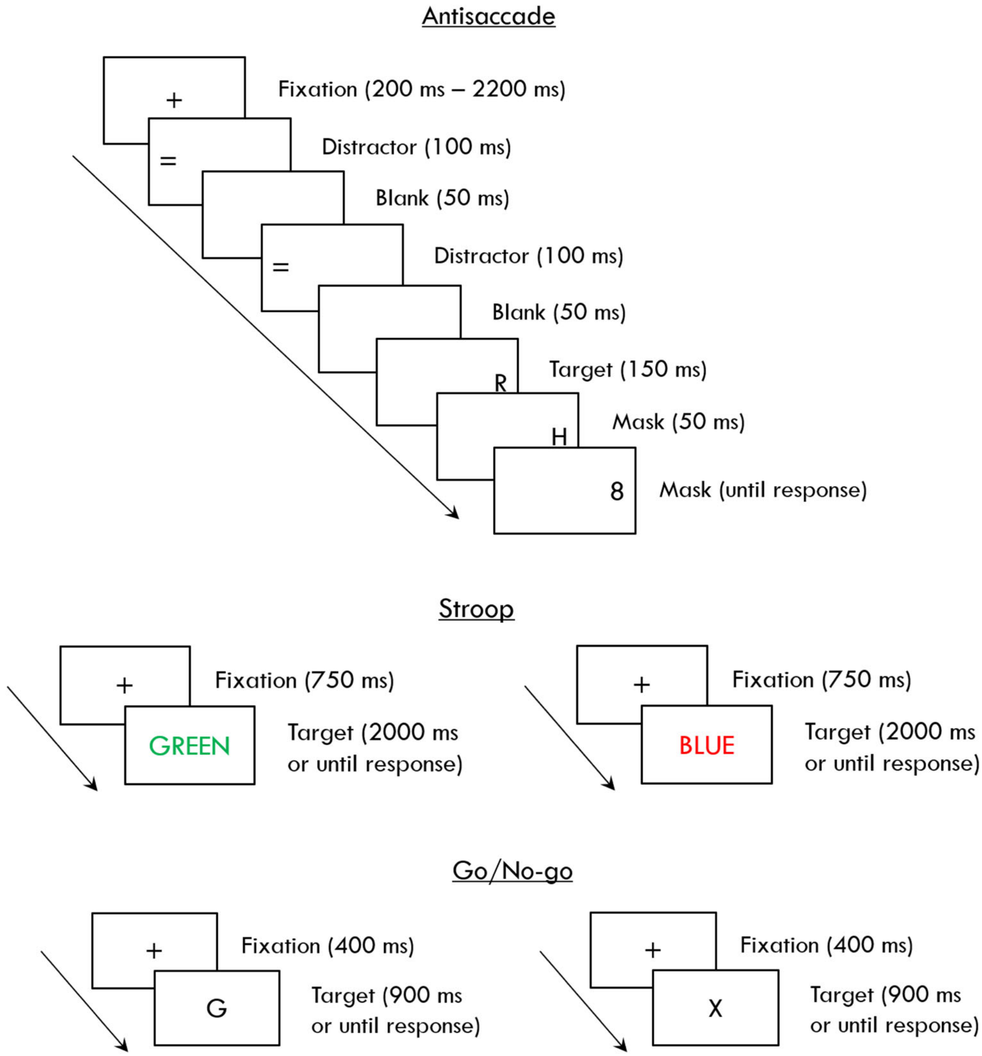
[g] Extraversion and neuroticism were coded as mean scores from the mini International Personality Item Pool-Five-Factor Model measure (Donnellan et al., 2006).

24 practice and 72 main test trials. The proportion of correct responses on the antisaccade trials represented better performance.

Go/No-Go. We adapted the go/no-go task from Redick et al. (2011). We asked participants to respond as quickly and accurately as possible on the keyboard according to a letter (either X or non-X) shown on the computer screen. Participants had to press the spacebar in response to non-X letters (go trials), but refrain from pressing the key in response to the target X letter (no-go trials). In every trial, a letter stimulus was first shown for 400 ms, and thereafter a blank screen was shown for 900 ms or until a response key was pressed. The intertrial interval ranged from 400 ms to 1300 ms. We had 445 go trials and 55 no-go trials, which meant that the target stimulus was infrequently presented (11% of the time). A higher proportion of correct responses on the no-go trials indicated better performance.

Stroop. We adapted the task from Unsworth and McMillan (2014). Participants were directed to indicate the colour of a word as quickly and accurately as possible by pressing

Fig. 1 Trial Sequence of Inhibition Tasks



Note. The top, middle, and bottom panels depict the trial sequences of the antisaccade, Stroop, and go/no-go tasks, respectively. For the Stroop task, examples of congruent and incongruent trials are shown in the left and right panels, respectively. For the go/no-go task, examples of go and no-go trials are displayed in the left and right panels, respectively.

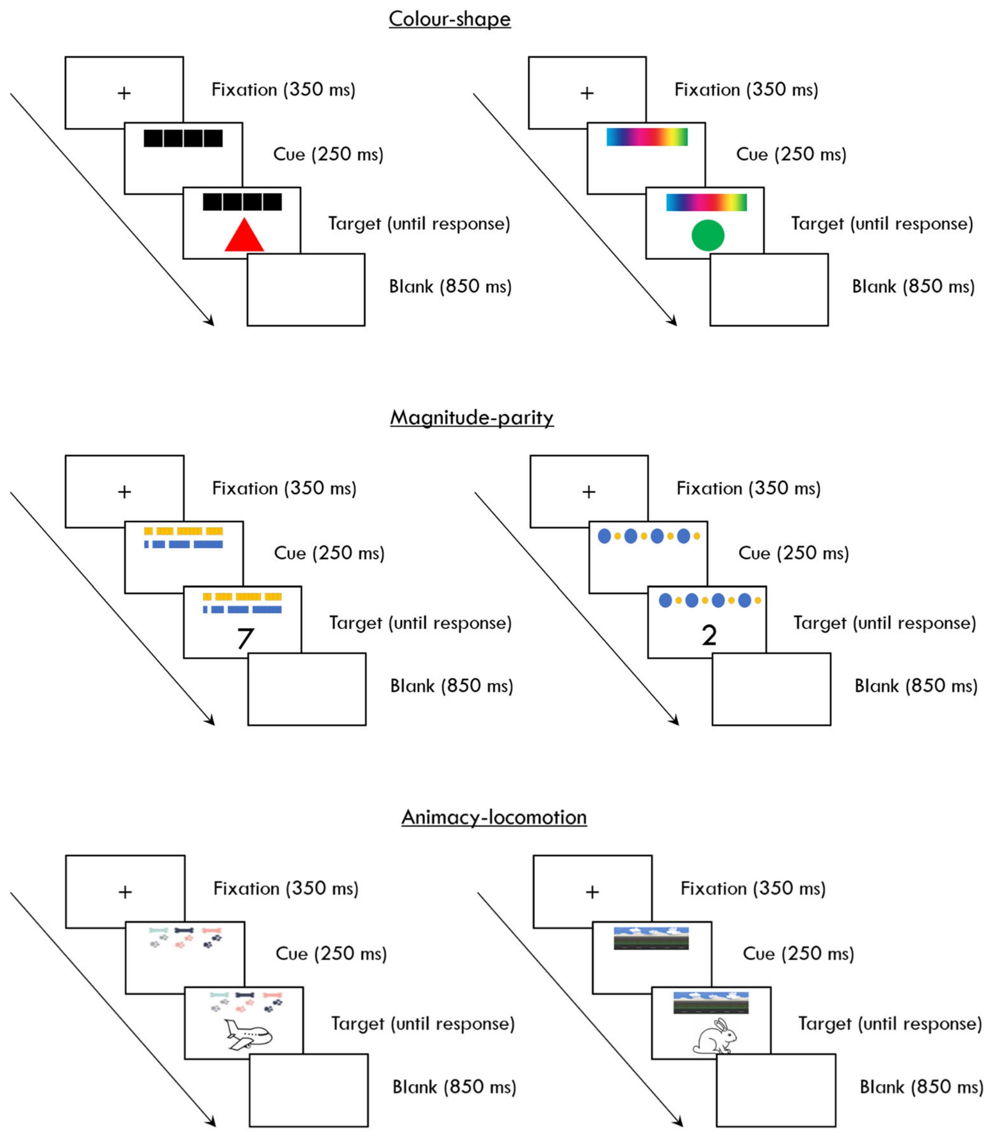
the R (for red), Y (yellow), G (green), or B (blue) key, while ignoring the word (e.g., "blue" printed in red ink). Each trial started with a fixation point (750 ms) followed by the target word, which remained on the screen for 2000 ms or until participants pressed a response key. To increase task difficulty, we administered a large proportion of congruent trials (144) in which the colour and meaning of the target were identical (e.g., "red" printed in red ink); only 72 of those were incongruent trials, with the target word in a different colour (e.g., "red" printed in blue ink). Ten practice trials were administered prior to the main task. To integrate both accuracy and RT scores, we used reverse-coded bin scores to index inhibition (see Binning Procedure), with higher values indicating better performance.

Shifting

We employed three shifting tasks based on the task-switching paradigm (see Fig. 2; Monsell, 2003). Performance on each shifting task was indexed by reverse-scored bin scores (see Results), with higher values denoting better performance.

Colour shape. Upon presentation of a given cue, participants were asked to sort a bivalent target (i.e., green circle or red triangle) according to its colour (green or red) or shape (circle or triangle). Two response keys were mapped to two different attributes of the bivalent targets (the *D* key for circle or red or the *K* key for green or triangle). Colour and shape rules were cued by a colour gradient and a row of black squares, respectively. In each trial, a fixation point was presented for 350 ms followed by a black screen for 150 ms, after

Fig. 2 Trial Sequence of Shifting Tasks



Note. The top, middle, and bottom panels represent the trial sequences of the colour-shape, magnitude-parity, and animacy-locomotion tasks, respectively. For the colour-shape task, the shape and colour cues are shown in the top-left and top-right panels, respectively. For the magnitude-parity task, the parity and magnitude cues are illustrated in the middle-left and middle-right panels, respectively. For the animacy-locomotion task, the animacy and locomotion cues are displayed in the bottom-left and bottom-right panels, respectively.

which the cue and the target were sequentially presented, with an interval of 250 ms in between. The cue and target remained on the screen until a response was entered. The inter-trial interval was 850 ms.

We administered four blocks (36 trials each), with an equal number of switch trials (e.g., colour rule followed by shape rule) and repeat trials (e.g., shape rule for two consecutive trials). Trial order was randomised, with the condition that up to four repeat trials could be consecutively presented. We administered 80 switch trials and 80 repeat trials, and the first trial in each block was excluded from analysis.

Magnitude Parity. Depending on a given cue, participants were asked to sort bivalent target numbers—2 (an even number less than five) and 7 (an odd number more than five)—by either its magnitude (smaller or greater than five) or parity (odd or even number). Participants pressed the *D* key for an odd number or being smaller than five or the *K* key for an even number or being greater than five. The magnitude rule was cued by a row of circles that varied in size and the parity rule by rows of odd-numbered and even-numbered squares. All other methodological aspects were identical to the colour-shape task.

Animacy Locomotion. Upon presentation of the cue, participants were instructed to sort a target (plane or rabbit) according to its animacy (animate or inanimate) or locomotion (flying or nonflying) attributes by pressing either the *D* (animate or flying) or *K* (inanimate or nonflying) key. The animacy rule was cued by a picture of dog paws, and the locomotion rule by a picture of roads and skies. All other methodological aspects were identical to the colour-shape task.

Working Memory

To assess working memory (i.e., the ability to mentally retain and process information), we adapted Foster et al.'s (2015) complex span tasks that contained distractor and memory components (encoding to-be-remembered items). Using the partial-credit load (PCL) procedure, performance on these tasks was indexed by the proportion of correctly remembered items out of the total number of to-be-remembered items; higher values reflected better performance.

Operation Span. Participants were presented with a series of target letters (memory task) at a rate of 800 ms per item for a later recall test. Each target letter was preceded by a simple arithmetic operation (e.g., (2×3) $-1 = 5$), which served as a distractor task that required participants to verify its correctness. After presentation of a series of arithmetic operations and to-be-remembered letters, participants were shown a 4×3 matrix of letters and asked to click the appropriate letters in the correct order. The recall task remained on screen until participants completed their responses. The set size (i.e., the total number of letters to be recalled) of a trial varied from three to seven and was randomly presented across trials.

Rotation Span. Participants were presented with an arrow that pointed in one of eight directions and was either short or long and asked to remember its length and directionality for the later recall task. The presentation of each arrow was preceded by a distractor task, in which participants had to indicate whether a rotated letter was presented correctly in an upright orientation or as its mirror image. During the recall period, participants were presented with a diagram displaying 16 arrows that varied in direction and length and directed to choose the previously presented arrow stimuli in the correct order. The total number of arrows to recall (i.e., set size) ranged from two to five per trial and was randomised across two blocks of trials. All other methodological aspects were similar to the operation-span task.

Symmetry Span. Participants were presented with a series of red squares on a 4×4 grid and asked to remember the location of each. Presentation of each red square was preceded by a distractor task in which participants were instructed to indicate whether a geometric figure was symmetrical along its vertical axis. During the recall, participants were presented with the same 4×4 grid (without the red squares) on the screen and asked to recall the positions of the previously presented red squares in the correct order. The set size of each symmetry-location sequence varied from two to five per trial and was randomised across two blocks of trials. All other methodological details were identical to the operation-span task.

Covariates

Nonverbal fluid intelligence was assessed by the 9-item short form of Raven's Standard Progressive Matrices (RSPM-SF; Bilker et al., 2012). Participants were presented with illustrations of concrete or abstract figures and asked to solve visual analogies of target stimuli. A higher number of correct responses reflected better fluid intelligence. Extraversion (e.g., "I talk to a lot of different people at parties") and neuroticism (e.g., "I have frequent mood swings") were assessed using 4-item subscales (1 = *strongly disagree*, 5 = *strongly agree*) from the mini International Personality Item Pool-Five-Factor Model measure (Mini-IPIP; Donnellan et al., 2006), whereby higher mean scores denote greater levels of extraversion and neuroticism.

Procedure

The study was conducted across three 1-h sessions, with a 1-day interval between sessions. During the first session, participants completed a demographic questionnaire and the RSPM-SF as a measure of nonverbal intelligence. In the second session, we administered smartphone questionnaires and the operation-span, antisaccade, colour-shape, and rotation-span tasks. Lastly, the magnitude-parity, go/no-go, symmetry-span, animacy-locomotion, and Stroop tasks were administered in the third session. Following past research on individual differences in EF (e.g., Miyake et al., 2000), the order of EF tasks was fixed to minimise potential participant-by-order interactions, thereby allowing for individuals' scores to be more directly comparable. To attenuate practice effects, we ensured that no two consecutive tasks assessed the same EF facet. Further, a 2-min break was administered between each EF task to minimise fatigue effects.

Analytic Strategy

Considering the well-established merits of bin scores (see Draheim et al., 2016), we used bin scores to index performance on the Stroop and shifting tasks. Following Draheim et al.'s (2016) procedures, we computed bin scores in five steps. First, we excluded trials based on the following criteria: (a) incorrect trials, (b) trials with RTs faster than 200 ms, and (c) trials with RTs that departed from each participant's mean RT by more than 3 *SD*. Second, at the within-subject level, each participant's mean RT for the baseline condition (i.e., congruent trials for the Stroop task and repeat trials for the shifting tasks) was subtracted from the RT of *every accurate trial* in the critical condition (i.e., incongruent trials in the Stroop task or switch trials in the shifting tasks). Third, at the between-subject level, all participants' trial-based difference scores computed above were rank-ordered into deciles and assigned bin values ranging from 1 to 10, with 1 containing the fastest 10% and 10 the slowest 10%. Therefore, a bin value of 1 for a particular trial indicates that the participant was faster than 90% of other participants' responses. Fourth, in the calculation of accuracy bin scores, each inaccurate trial from the critical condition (i.e., incongruent trials for the Stroop task and switch trials for the shifting tasks) was assigned a bin value of 20. The inclusion of inaccurate trials, relative to the reliance on RT scores alone, has been shown to improve reliability and validity, yield better detection of relations with other cognitive control measures, and is more robust to variations in research paradigms (e.g., individual-difference research versus experimental research; Hughes et al., 2014). Further, while assigning a bin value of 20 for every inaccurate trial appears arbitrary, past research (Draheim et al., 2016; Hughes et al., 2014) has shown that using different weights (e.g., 15 or 50) for inaccurate trials does not substantially alter correlations between bin scores and other constructs. Accordingly, these findings show that consideration of accuracy scores is more crucial than the precise weight given to accuracy. To integrate RT and accuracy scores, bin values across all accurate and inaccurate trials were averaged for each participant. Finally, each participant's bin score was reverse scored, with higher values denoting better performance.

We performed all analyses with M*plus* 7.4 (Muthén & Muthén, 2015), using the full information maximum likelihood procedure. All three EF facets and problematic smartphone tendencies were modelled as latent variables. Indicators for the inhibition latent factor were the accuracy scores for the antisaccade and go/no-go tasks, and bin scores for the Stroop task. Indicators for the working memory latent factor were partial-credit load scores for the operation-span, symmetry-span, and rotation-span tasks. Indicators for the shifting latent factor were bin scores for the colour-shape, magnitude-parity, and animacy-locomotion tasks. Indicators for the common EF factor were all nine EF tasks. Indicators for the problematic smartphone use latent factor were based on three parcels formed by the 10-item scale of the smartphone addiction scale (Kwon et al., 2013). Parcelling is suitable for unidimensional constructs and possesses psychometric and modelling-related advantages over item-level indicators (e.g., better distribution of the target construct across indicators and attenuation of random errors; Matsunaga, 2008). Daily smartphone screen time and smartphone checking frequency were modelled as manifest variables.

We first ensured that the indicators reflected their intended latent factors by evaluating the measurement models using confirmatory factor analyses. Next, structural equation modelling was performed by regressing all three EF constituents on smartphone screen time and smartphone checking frequency separately. Next, the moderator and covariates were added to the structural models to control for third-variable effects. To assess the moderating role of problematic smartphone use, we conducted latent moderated structural equation modelling by including the problematic smartphone use x smartphone screen time and problematic smartphone use x smartphone checking frequency interaction terms in their individual models. Significant interaction effects were further examined using the Johnson-Neyman procedure. In evaluating our models' fit to the data, we used the following criteria (Hair et al., 2009): root-mean-square error of approximation (RMSEA) values equal to or below .08 (acceptable) or .06 (good); standardised root-mean-squared residual (SRMR) values equal to or below .08 (good); and comparative fit index (CFI) close to or greater than .90 (acceptable) or .95 (good). All reported estimates were standardised. Zero-order correlations between all variables are presented in Appendix (Table 5).

Results

Measurement Model

Both the nested-factor EF model (Miyake & Friedman, 2012) and the problematic smartphone use model achieved a good fit to the data (see Table 2). To model the shared variance (i.e., common EF) among the three EF components (i.e., inhibition, shifting, and working memory), all nine EF tasks were used to extract a common EF factor, which reflects the general goal-management ability to sustain task-relevant information that is required in all types of EF tasks. Next, working-memory-specific and shifting-specific factors were extracted from the working memory and shifting tasks, respectively. Working-memory-specific and shifting-specific factors represent the demands unique to working memory (i.e., manipulating information within the mental workspace) and shifting (i.e., switching between various tasks) measures. Similar to Miyake and Friedman's (2012) nested-factor model, the inhibition-specific factor was not modelled, because there was no unique variance left in the inhibition tasks after the common EF factor had been extracted. All factor loadings were significant ($ps < .004$; see Fig. 3), which indicates that all indicators adequately represented their underlying latent constructs. We also assessed how the nested-factor model compared with alternative EF models. Importantly, the nested-factor EF structure was the best-fitting model relative to the one-, two-, and three-factor models (see Table 2). Together, our confirmatory factor analyses indicate that the EF and problematic smartphone use models provide a good fit to the data.

Structural Models

Regarding the structural models (see Table 3 for a summary), we found that smartphone screen time positively predicted working-

Table 2 Fit Indices for Measurement and Structural Models

	χ^2	*df*	RMSEA	SRMR	CFI
Measurement models					
EF					
One-factor model	124.50	27	.146	.090	.754
Two-factor models					
Inhibition-WM merged	93.80	26	.124	.092	.829
Inhibition-shifting merged	48.28	26	.071	.050	.944
WM-shifting merged	114.98	26	.142	.087	.775
Three-factor model	37.88	24	.068	.042	.965
Nested-factor model	33.24	21	.059	.039	.969
Problematic smartphone use[a]	0.00	0	.00	.00	1.00
Full measurement model[b]	54.40	45	.035	.042	.981
Structural models					
Smartphone screen time					
Unadjusted model	36.44	27	.045	.039	.977
Adjusted model with covariates[c]	149.12	113	.043	.057	.938
Smartphone checking frequency					
Unadjusted model	39.39	27	.052	.040	.969
Adjusted model with covariates[c]	132.08	113	.032	.055	.966

Note. WM = working memory; RMSEA = root-mean-square error of approximation; SRMR = standardised root-mean-square residual; CFI = comparative fit index.

[a] The measurement model was saturated, and thus the fit was perfect.

[b] The full measurement model includes both the nested-factor EF and problematic smartphone use models.

[c] Covariates were age, gender, socioeconomic status (household income), intelligence, extraversion, and neuroticism.

memory-specific ($\gamma = .29$, $SE = .09$, $p = .001$) and shifting-specific ($\gamma = .26$, $SE = .13$, $p = .038$) factors, but not common EF ($\gamma = -.14$, $SE = .10$, $p = .168$). When problematic smartphone use and covariates were added to the model, the predictive relations of smartphone screen time with working-memory-specific ($\gamma = .30$, $SE = .09$, $p < .001$) and shifting-specific ($\gamma = .27$, $SE = .12$, $p = .029$) factors remained significant (see Fig. 4). Next, our latent moderated structural equation modelling analyses revealed that none of the problematic smartphone use x smartphone screen time interactions were significant for common EF, working-memory-specific, or shifting-specific aspects of EF ($|\gamma| < .04$, *ps* > .72); this signifies that problematic smartphone tendencies do not moderate the effect of smartphone screen time on EF.

Smartphone checking frequency negatively predicted common EF ($\gamma = -.27$, $SE = .10$, $p = .006$) but positively predicted the shifting-specific factor ($\gamma = .36$, $SE = .16$, $p = .021$). The associations of smartphone checking frequency with common EF ($\gamma = -.27$, $SE = .10$, $p = .007$) and the shifting-specific factor ($\gamma = .52$, $SE = .17$, $p = .002$) remained significant, even when problematic smartphone use and covariates were controlled for (see Table 3 and Fig. 4). Subsequently, our latent moderation structural equation modelling analyses demonstrated that the problematic smartphone use x smartphone checking frequency interaction term was significant for common EF ($\gamma = -.24$, $SE = .09$, $p = .005$) but not for working-memory-specific or shifting-specific factors ($|\gamma|$s < .19, *ps* > .15). Specifically, the negative effect of smartphone checking frequency on common EF was more pronounced for higher levels (e.g., +1 *SD*), but not for lower levels (e.g., −1 *SD*), of problematic smartphone use (see Fig. 5). Therefore, the deleterious effect of smartphone checking frequency on common EF is magnified with higher levels of problematic smartphone tendencies.

Additionally, of the covariates, higher levels of fluid intelligence were consistently associated with better common EF and working-memory-specific abilities across both structural models (Friedman et al., 2008). No other covariates were consistently related to the three EF components.

As an exploratory analysis, we examined the relations between smartphone use and the reaction time coefficient of variation (RTCV; i.e., ratio of the standard deviation to the mean) for the go/no-go and Stroop tasks, which have previously been used to investigate reaction time variability (e.g., goal neglect, mind-wandering, attentional lapses; Kofler et al., 2013; Smallwood & Schooler, 2006; Smallwood et al., 2008).

We found that the latent factor comprising the RTCV scores for the go/no-go and Stroop tasks was positively correlated with problematic smartphone use ($\varphi = .34$,

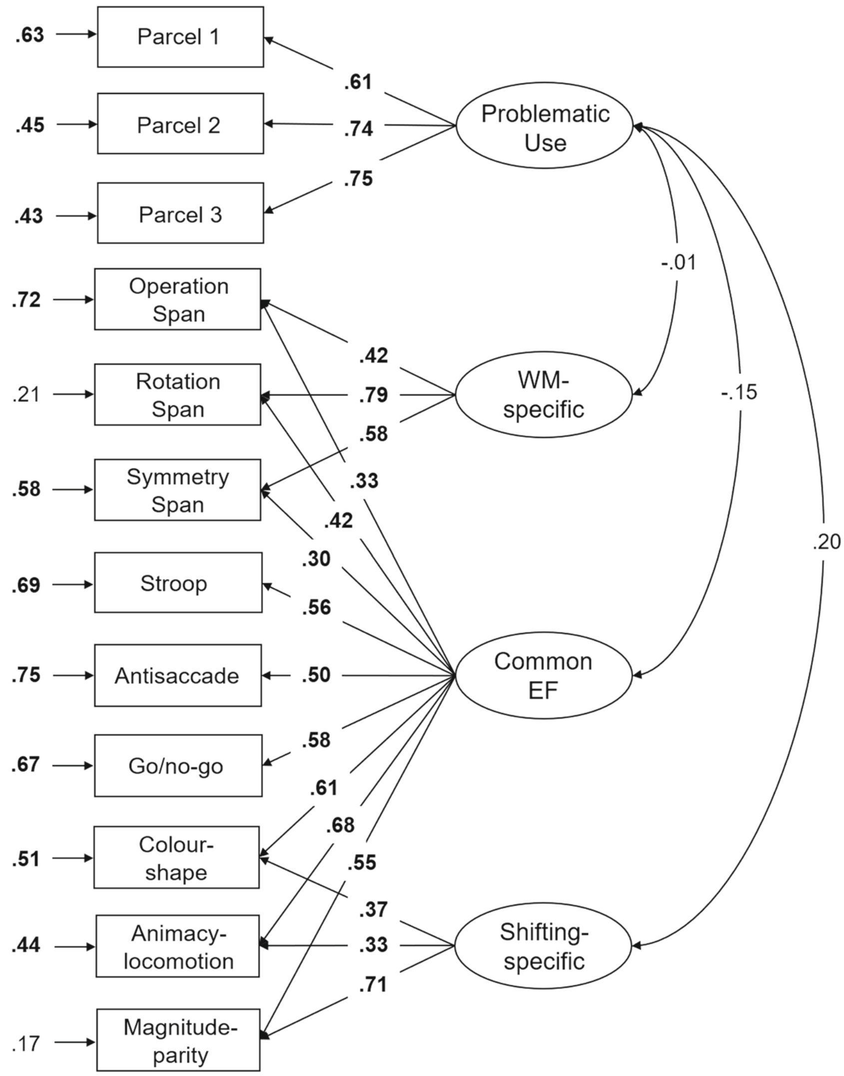


Fig. 3 Full Measurement Model for EF and Problematic Smartphone Use with Standardised Estimates

Note. Ovals denote latent factors and rectangles represent manifest variables. Values for longer, single-headed arrows indicate factor loadings; values for shorter, single-headed arrows signify error variances; values for double-headed arrows denote interfactor correlations. WM = working memory. All factor loadings and residual variances were statistically significant (as marked in boldface), except for the residual variances for rotation span ($p = .16$) and magnitude-parity ($p = .39$) tasks. Interfactor correlations, represented by curved, double-arrow values, between problematic smartphone use and the three EF facets were not significant (ps > .09).

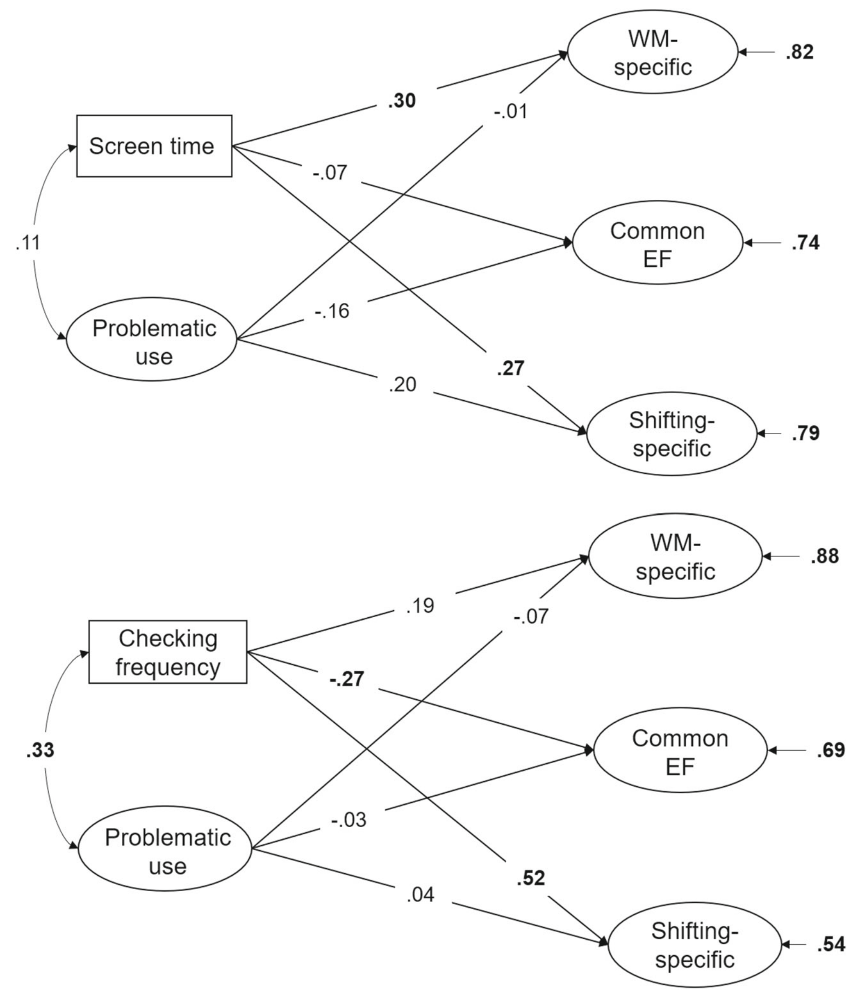
$SE = .16$, $p = .035$) but not checking frequency ($\varphi = .22$, $SE = .12$, $p = .060$) or screen time ($\varphi = .02$, $SE = .11$, $p = .847$). These results indicate that a greater extent of inattention (i.e., RT variability) corresponds to higher levels of problematic smartphone use, but not checking frequency or screen time. However, it should be noted that RTCV scores may imply different forms of inattention, depending on the tasks employed. For instance, RT variability may indicate boredom on a relatively simple task or preoccupation with task demands on a more challenging task. Since the go/no-go and Stroop tasks differ in task demands, the theoretical interpretation of the latent factor that reflects the RTCV scores for the go/no-go and Stroop tasks is unclear. Therefore, we present the correlations between the smartphone use indices (i.e., screen time, checking frequency, and problematic tendencies) and the two RTCV scores for the go/no-go and Stroop tasks separately. Specifically, higher RTCV scores on the go/no-go task were correlated with greater smartphone checking frequency and

Table 3 Standardised Parameter Estimates of Structural Models for Smartphone Screen Time and Checking Frequency

	Screen time			Checking frequency		
	CEF	WM-specific	Shifting-specific	CEF	WM-specific	Shifting-specific
Focal predictor						
Smartphone use	−.07 (.10)	**.30 (.09)**	**.27 (.12)**	**−.27 (.10)**	.19 (.11)	**.52 (.17)**
Moderator						
Problematic use	−.15 (.11)	−.01 (.11)	.19 (.14)	−.02 (.12)	−.08 (.12)	.01 (.18)
Covariates						
Age	.08 (.11)	.05 (.11)	.01 (.14)	.01 (.11)	.10 (.11)	.12 (.15)
Gender	.09 (.12)	−.06 (.11)	−.21 (.15)	.18 (.12)	−.13 (.12)	**−.45 (.18)**
Income	−.10 (.10)	−.07 (.09)	.20 (.12)	−.08 (.09)	−.11 (.09)	.17 (.14)
Intelligence	**.42 (.09)**	**.31 (.10)**	.05 (.14)	**.41 (.09)**	**.28 (.10)**	−.06 (.17)
Extraversion	.07 (.10)	−.05 (.09)	−.18 (.12)	.06 (.09)	−.04 (.09)	−.19 (.13)
Neuroticism	.14 (.10)	−.12 (.10)	−.04 (.12)	**.19 (.09)**	−.17 (.10)	−.20 (.15)

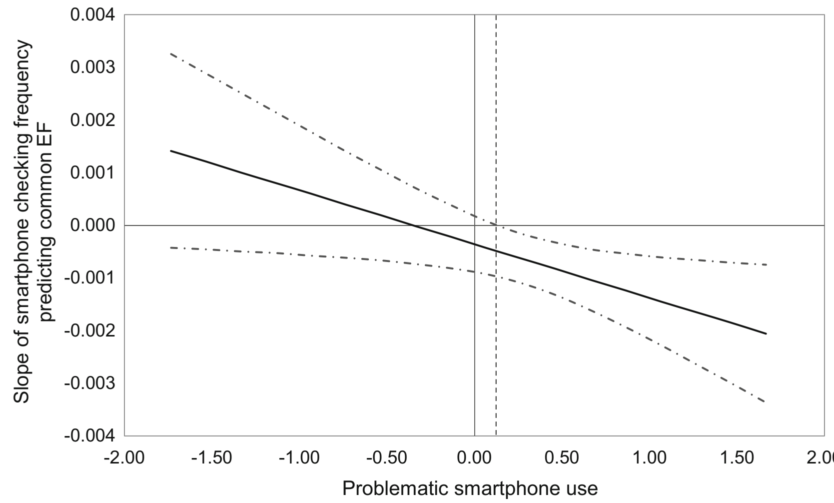
Note. Values denote standardised estimates with standard errors in parentheses. Significant values are marked in boldface; $p < .05$. CEF = common EF; WM = working memory

Fig. 4 Structural Models for Smartphone Screen Time and Checking Frequency with Standardised Estimates



Note. Ovals signify latent variables and rectangles denote manifest variables. Values for longer, single-headed arrows represent path coefficients; values for shorter, single-headed arrows indicate residual variances; values for double-headed arrows specify correlations between exogenous variables. WM = working memory. Significant estimates are in boldface, $p < .05$.

Fig. 5 Moderation Analysis using the Johnson-Neyman technique



Note. This Johnson-Neyman plot depicts the slope of smartphone checking frequency predicting common EF (represented by the solid line, with dash-dot lines indicating 95% confidence intervals) against values of problematic smartphone use (mean-centred), which range from -1.72 (-3 *SD*) to +1.72 (+3 *SD*). The negative effect of smartphone checking frequency on common EF was significant at the problematic smartphone use (latent factor) value of 0.13 (i.e., +0.22 *SD*; as indicated by the vertical dashed line) and higher.

problematic tendencies; conversely, RTCV scores on the Stroop task were not related to the three smartphone use indices (see Table 4).

Discussion

This study investigated the effects of smartphone screen time, checking frequency, and problematic smartphone tendencies on EF. Our findings show that various operationalisations of smartphone use are asymmetrically related to the three EF facets. For instance, we found that smartphone screen time was positively associated with the shifting-specific and working-memory-specific aspects of EF. These findings suggest that smartphone use entails proficient switching between different applications or the information and attentional processing of incoming stimuli (e.g., text notifications) on smartphones while mentally maintaining or updating the current state of the interrupted or ongoing application. Considering the increasingly pivotal role of smartphones in managing everyday demands across work, academic, and social domains, our findings are congruent with the idea that efficient smartphone use implicates higher-order cognitive processes, such as shifting and working memory (Alloway & Alloway, 2012; Alzahabi & Becker, 2013; Leiva et al., 2012). Our findings qualify prior assertions that smartphone use is generally concomitant with negative cognitive outcomes (Ellison, 2012) by showing that smartphone screen time is positively, rather than negatively, associated with certain aspects of EF in college students.

However, we found a striking dissociation between smartphone checking frequency and two EF processes. Specifically, frequent smartphone checking was related to better shifting-specific, but poorer common EF, abilities. On the one hand, shifting abilities facilitate disengagement from the current task to check updates and notifications on one's smartphone, which dovetails with previous findings that habitual switching between different media formats entails more effective shifting abilities (Alzahabi & Becker, 2013). On the other hand, persistent smartphone checking likely reflects

Table 4 Correlations Between Smartphone Use Indices and Reaction Time Variability for Stroop and Go/no-go Tasks

	1	2	3	4
1. Smartphone screen time	–			
2. Smartphone checking frequency	**.43**	–		
3. Problematic smartphone use	.12	**.33**	–	
4. Stroop	.10	.07	.15	–
5. Go/no-go	−.01	**.17**	**.26**	**.27**

Note. Reaction time variability was indexed by the coefficient of variation. Significant correlations marked in boldface, $p < .05$

behavioural impulsivity, as manifested by impoverished sustained attention and goal maintenance. This finding is in line with prior research showing the detrimental effects of smartphone alerts and notifications, which—akin to smartphone checking—are attentionally disruptive and, consequently, impair goal maintenance and task productivity (Oulasvirta et al., 2011; Stothart et al., 2015). Consistent with the literature that highlights the opposing relations of common EF and shifting with behavioural outcomes (e.g., rumination; Altamirano et al., 2010), our findings support the notion of a trade-off between mental stability and flexibility, whereby weaker goal representations are more easily and quickly replaced by new goals (Friedman & Miyake, 2017). Importantly, our findings demonstrate that habitual smartphone checking frequency is oriented toward constant switching between tasks at the expense of sustained attention to a focal task.

In line with past work on the interactive effects of problematic smartphone use with smartphone presence and separation on EF processes (Hartanto & Yang, 2016; Ward et al., 2017), we found that problematic smartphone use moderated the relation between checking frequency and common EF. Specifically, smartphone checking frequency was associated with more impaired common EF for higher, but not lower, levels of problematic smartphone tendencies. These results imply that for individuals with higher problematic smartphone tendencies, frequent smartphone checking may reflect an impulsive habit that impedes the ability to remain focused on important and goal-relevant tasks (e.g., browsing social media during class). However, for those who have lower levels of problematic smartphone tendencies, checking may denote purposive and well-regulated actions that do not negatively detract from or disrupt goal maintenance and progress (e.g., keeping track of work-related emails at work). In this regard, our moderation findings may account for some of the inconsistent evidence on the relation between smartphone use and inhibition. Specifically, it is plausible that the null results of previous studies may be due to the reliance on undergraduate samples with lower levels of problematic smartphone use (e.g., Chen et al., 2016; Johannes et al., 2019; Pluck et al., 2020). Crucially, our moderation results demonstrate that the detrimental effect of checking frequency on common EF is dependent on the extent to which problematic smartphone use hampers attentional focus and performance for ongoing tasks.

We found that problematic smartphone use was not related to any of the EF facets. Though somewhat surprising, our findings replicate previous work that has failed to find associations between problematic smartphone use and EF (e.g., inhibition; Chen et al., 2016; Gao et al., 2020; Hadar et al., 2017; Pluck et al., 2020). A possible explanation is that these null findings were based on undergraduate samples with peak cognitive functioning and predominantly nonclinical levels of problematic smartphone tendencies (e.g., Chen et al., 2016; Johannes et al., 2019; Pluck et al., 2020). For instance, 67.1% of our undergraduate sample reported nonclinical levels of problematic smartphone use, based on the cutoff scores established by Kwon et al. (2013). Further, it should be noted that Kwon et al.'s clinical cutoff scores were delineated using adolescent samples, who may differ in smartphone habits and motivations for smartphone use (e.g., gaining peer acceptance; Lee & Lee, 2017) compared with undergraduate cohorts. Moreover, given that smartphone use is now more widespread than ever before, Kwon et al.'s clinical cutoff scores may not accurately reflect smartphone use in today's context. Therefore, future research should investigate the cognitive profiles of populations with greater variation in problematic smartphone tendencies using age-appropriate clinical cutoffs.

Our findings are incongruent with previous findings that have shown negative associations of smartphone use with working memory (Abramson et al., 2009; Ward et al., 2017) and shifting (Ophir et al., 2009; cf. Pluck et al., 2020). Such discrepancies could be attributed to the methodological approaches we adopted in this study. First, our use of latent-variable analysis minimises the task-specific idiosyncrasies inherent to EF tasks. For instance, at the individual-task level, we found that screen time was related to the Stroop and rotation-span tasks, while checking frequency was associated with the go/no-go task. Problematic smartphone use was not associated with any of the EF tasks. These findings indicate inconsistent relations between the different indices of smartphone use and EF tasks that are supposed to measure the same construct. Hence, results based on a single-task EF measure may not necessarily generalise to other construct-similar EF tasks. Second, given that working memory and shifting comprise both common EF (i.e., shared variance among all EF factors) and construct-specific (i.e., working-memory-specific and shifting-specific) aspects, previous studies were unable to determine whether the negative relations of smartphone use with working memory and shifting were driven by common EF and/or the unique components attributed to working memory and shifting. Therefore, our use of the nested-factor model allows us to identify the specific components of EF that would be affected by smartphone use: Smartphone screen time is positively linked to the working-memory-specific and shifting-specific aspects of EF, but not common EF. Crucially, these findings underscore the need for future research to adopt latent-variable and nested-factor approaches to allow for purer and more precise estimates of the EF constructs of interest.

Several limitations of our study should be acknowledged. First, given the correlational design of our study, causal inferences are limited. Specifically, although smartphone use variables were used as predictors of EF in our models, it is possible that EF may instead influence smartphone use. For instance, more proficient working-memory-specific and shifting-specific abilities may afford better mental updating of task-relevant information (e.g., status updates, checking emails, etc.) and ease in switching from one application to another. Likewise, poorer common EF may engender greater susceptibility to interference from smartphone updates and notifications (i.e., checking frequency). Hence, future work should employ more controlled experimental designs and longitudinal analyses to ascertain the directionality of the links between EF and the various indices of smartphone use.

Second, although screen time is a commonly employed indicator of smartphone use (e.g., Andrews et al., 2015), it may be somewhat generic; therefore, we were unable to shed light on the specific aspects of smartphone screen time that are linked to EF facets. To this end, further research is warranted to perform more fine-grained assessments of screen time (e.g., time spent on different types of smartphone applications) to better understand how screen time for specific smartphone activities affects EF. Further, our study did not specify the nature of smartphone checking. For instance, individuals who immediately check and respond to notifications may form a habit of frequent checking that is disruptive to current goals (Oulasvirta et al., 2011). Accordingly, dissociating immediate checking and responding in smartphone use is an avenue that future studies can investigate.

Third, given the reporting biases associated with self-reported data (Paulhus & Vazire, 2007), the obtained estimates for smartphone use variables may not accurately reflect actual use. For instance, in a study by Andrews et al. (2015), the actual frequency of smartphone checking was higher than self-reported estimates, whereas the actual and self-reported estimates of screen time were comparable with each other. In contrast, Junco (2013) demonstrated that self-reported and actual time spent on Facebook were significantly discrepant, thereby highlighting the inaccuracy of self-report measures. Therefore, estimates of checking frequency and screen time in our study may have been underestimated. Accordingly, future research should verify our results using objective assessments of smartphone screen time and checking frequency (e.g., the Screen Time and Digital Wellbeing application; Apple, 2020; Google, n.d.).

Fourth, our findings are based on undergraduate samples and, therefore, may have limited generalisability. For instance, our sample may differ from adolescent samples with respect to smartphone habits and motivation (Kwon et al., 2013; Lee & Lee, 2017). Further, younger individuals with higher education and income, such as those in our sample, are likely to use smartphones more frequently than older adults (Kim et al., 2015). Thus, further replications of our findings with non-university samples from other age groups (e.g., adolescents and middle-aged adults) are warranted.

Conclusion

The ubiquity of smartphones among young adults has sparked concerns regarding the potentially deleterious impacts of habitual smartphone use on cognitive processes, such as EF (Wilmer et al., 2017). Our findings qualify such concerns by demonstrating that the effect of smartphone use on EF is contingent on specific aspects of smartphone engagement (i.e., screen time, checking frequency, and problematic smartphone use). Specifically, screen time may not always be negatively associated with impaired EF. Prolonged screen time may benefit shifting and working memory abilities, since switching between applications requires that individuals hold the interrupted content in mind. However, we caution against frequent checking, because it can be disruptive and may impair one's ability to maintain current goals (i.e., common EF). Importantly, individuals should be mindful of problematic smartphone reliance that can further hamper one's common EF. However, we note that although some researchers advocate for the recognition of problematic smartphone use (Potenza et al., 2018), others argue against diagnosing it as addictive pathology due to the lack of information prior to the reification of a diagnosis (News Media, Public Education and Public Policy Committee, 2018). Hence, caution should be taken not to interpret the conceptualisation of problematic smartphone use as pathological dependency or addictive symptoms (Billieux et al., 2015).

Our findings hold practical implications for policies and interventions that aim to circumvent impairments in cognitive functioning (e.g., attentional focus) by curtailing smartphone use, especially in educational settings. Specifically, considering the asymmetric effects of the different indices of smartphone use on EF, our results imply that checking frequency and problematic use, rather than screen time, are the most promising candidates for intervention studies. Importantly, our results underscore the need to recognise the construct distinctiveness of the various markers of smartphone use in order to better elucidate the consequences of smartphone use for cognitive processes.

Appendix

Table 5 Zero-Order Correlations between Variables of Interest

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Smartphone screen time	–																
2. Smartphone checking frequency	**.43**	–															
3. Problematic smartphone use	.12	**.30**	–														
4. Antisaccade	−.01	−.03	−.12	–													
5. Go/no-go	−.07	**−.19**	−.08	**.31**	–												
6. Stroop	**−.16**	−.14	−.05	**.31**	**.33**	–											
7. Operation span	.05	−.06	.05	**.29**	**.16**	.12	–										
8. Rotation span	**.17**	−.04	−.05	**.30**	.13	**.20**	**.45**	–									
9. Symmetry span	.14	.03	−.09	.14	**.16**	.11	**.32**	**.58**	–								
10. Colour-shape	.07	.05	−.03	**.29**	**.33**	**.36**	**.22**	**.22**	**.25**	–							
11. Animacy-locomotion	.02	−.14	−.02	**.24**	**.42**	**.39**	**.23**	**.36**	**.22**	**.53**	**–**						
12. Magnitude-parity	.08	.05	.05	**.24**	**.35**	**.25**	**.19**	**.30**	**.19**	**.59**	**.60**	–					
13. Age	.06	−.08	.01	.08	.11	.03	.06	.09	.11	.01	.06	.01	–				
14. Gender	.03	.08	−.10	**.17**	.15	−.01	.09	.09	.08	−.06	.06	−.03	**.57**	–			
15. Income	−.11	.06	−.12	.10	−.09	.03	−.04	−.07	−.03	.05	−.07	.11	−.15	−.14	–		
16. Intelligence	−.12	−.07	−.03	**.38**	**.17**	**.19**	**.33**	**.32**	**.26**	**.24**	**.31**	**.27**	.03	.13	.11	–	
17. Extraversion	.05	.08	−.01	.13	−.01	−.01	−.02	.01	−.02	−.01	−.07	−.06	−.03	−.01	**.19**	.03	–
18. Neuroticism	−.05	.10	**.18**	−.11	.03	.07	−.01	−.09	−.06	.01	.13	.05	**−.21**	**−.24**	−.11	−.04	**−.23**

Note. Significant correlations marked in boldface, $p < .05$. Gender was coded as 0 = *female*, 1 = *male.*

Code Availability Code will be available upon request.

Authors' Contributions The authors confirm contribution to the paper as follows: study conception and design by W. X. Toh and H. Yang; data collection by W. X. Toh; data analysis by W. X. Toh; interpretation of results by W. X. Toh and H. Yang; draft manuscript preparation by all authors.

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Data Availability Data and material will be available upon request.

Declarations

Conflicts of Interest/ Competing Interests Not applicable.

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