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Ana C. Ruiz Pardo
Western University

John Paul Minda
Western University, jpminda@uwo.ca

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Reexamining the “brain drain” effect: A replication of Ward et al. (2017)

Ana C. Ruiz Pardo *, John Paul Minda

Department of Psychology & The Brain and Mind Institute, Western Interdisciplinary Research Building, Western University, London, ON N6A 5C2, Canada

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ABSTRACT

The present study was a pre-registered direct replication of Ward et al.'s (2017) second experiment (OSF pre-registration found at: https://osf.io/5fq4r). This replication assigned both smartphone location (on desk, in pocket/bag, or outside of the testing room) and smartphone power (on, or off) for a total of six conditions. Participants completed an automated operation span (OSpan) task, a Cue-Dependent Go/No-Go task, and the smartphone attachment and dependency inventory. It was hypothesized that performance on an attention-demanding task (i.e., the OSpan task) would be worse for those in closer proximity to their smartphone (on desk) and that those with greater smartphone attachment and dependency would have a larger “brain drain” effect. Using the same tasks and conditions as in Ward et al.'s (2017) second experiment, the present study found that the “brain drain” effect did not replicate: there was no difference between smartphone location conditions on performance on either the o-span task or the go/no-go task. These findings demonstrate that the mere presence of one's smartphone may not be enough to affect cognitive performance. Understanding these effects is crucial in a time where smartphones are a basic necessity.

1. Increased smartphone prevalence

Smartphones provide an easy and effective method of communicating with the world right at our fingertips. They have become a staple in most people's everyday life: in North America, smartphone ownership has gone from 77 % in 2016 to 81 % in 2019 (Pew Research Center, 2019). The World Health Organization (2015) reported that “behavioural addictions” associated with internet and smartphone use have occurred comorbid with some psychopathology (e.g., hyperactivity disorder and major depression) and health conditions (e.g., substance use disorders and insomnia). Therefore, there has been an increase in research investigating the possible effects of smartphone use on cognition. Additionally, an influx of smartphone research has also led to policy changes. For example, the Ontario government banned cell phones and smartphones in high schools based on the idea that these devices could distract students from their academic work (Jones, 2019). Such policy changes should be based on accurate and reproducible data. An overview of smartphone research, including the “brain drain” effect (i.e., reduced cognitive performance when one's smartphone is closer in proximity as defined by Ward et al., 2017), is presented. The present study's main goal was to investigate if the “brain drain” effect found in Ward et al.'s (2017) second experiment replicated.

1.1. Smartphone research

Smartphone availability is a relatively recent phenomenon, and research into its effects on cognition have been even more recent. Researchers looked first at the effects of smartphones on attention. Previous research has found attentional costs of smartphone usage during driver performance (Caird et al., 2014). However, the rising prevalence of smartphones has prompted research about how they can impact other cognitive abilities (Stothart et al., 2015; Thornton et al., 2014; Ward et al., 2017; Wilmer & Chein, 2016). This research includes investigating how smartphone use (Stothart et al., 2015; Wilmer & Chein, 2016) and smartphone presence (Thornton et al., 2014; Ward et al., 2017) can impact cognition. Smartphone use has been linked with depletion in cognitive function during day-to-day self-regulation (Wilmer & Chein, 2016). It was found that heavier mobile device users tended to have lower impulse control and a weaker tendency to delay gratification (Wilmer & Chein, 2016). These are just some examples of a growing field which investigates the effect of smartphone presence on cognition.

Smartphone presence research has taken many forms, one of which focused on how separating participants from their smartphone while receiving an unexpected notification such as a call or text. Stothart et al. (2015) addressed the impact of smartphone notification on cognitive resources. They found that receiving notifications affected performance

* Corresponding author.
E-mail addresses: aruizpar@uwo.ca (A.C. Ruiz Pardo), jpminda@uwo.ca (J.P. Minda).

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on an attention-demanding task. Participants were randomly assigned to one of three conditions: call notification, text notification, or no notification. Those in the notification conditions received a notification during the second block of the main task (Stothart et al., 2015). They showed that, even with no direct contact with a smartphone, participants performed worse under the notification conditions when compared to the no notification condition on a sustained attention to response task (i.e., a go/no-go task). Additionally, Clayton et al. (2015) found that separation from one's phone led to psychological and physiological anxiety: participants who were unable to answer their ringing phone (which was within viewing distance) during a wordsearch puzzle reported feeling increased anxiousness and unpleasantness, and showed higher physiological measures for anxiety (e.g., heart rate and blood pressure). These studies begin to depict how smartphone presence, specifically separation from one's smartphone, showed an effect on participant cognitive performance.

Next, some researchers looked specifically at smartphone presence by separating participants from their smartphone without using notifications during the task. Thornton et al. (2014) found that smartphones can affect performance on difficult tasks. In study one, participants were tested in pairs (i.e., each sitting on their own desk and facing away from each other) and told that they would complete several tasks that required attention and concentration to complete successfully. For each pair of participants, one would have the experimenter's smartphone (experimental) and the other would have a similar-sized notebook (control) placed on the edge of the table. In study two, participants were tested in a group setting (i.e., a classroom with around 20 students) and were randomly assigned to either place their cell phone on their desk (experimental) or nothing about their cell phones (control). For both study one and two, participants completed two-digit cancellation tasks (i.e., measured attention, cognitive capacity, and executive functioning), two trail making tasks (i.e., required attentional processes, mental flexibility, and motor function), and two brief questionnaires (i.e., measuring attentional difficulties and cell phone use and possession). Each task had two versions to each task in order to compare performance on an easier and a difficult version of each task. The digit cancellation task was either the normal/easier (i.e., cross out the target number; 90s) or additive/difficult (i.e., cross out the target number and any adjacent numbers that add up to the target; 180 s) version. The trail making task required participants to draw a line connecting either numbers sequentially (i.e. easy; e.g. 1-2-3-4-) or alternating numbers and letters sequentially (i.e., difficult; e.g., 1-A-2-B-3-C-4-D-) for 15 s. Results in both studies demonstrated a detriment associated with smartphone presence on the harder, resource-intensive versions of the tasks and no effect on the simpler versions of the same tasks (Thornton et al., 2014). Contrastingly, Hartanto and Yang (2016) found that smartphone separation (i.e., participants who were away from their smartphones) led to significantly worse performance on a measure of task switching (i.e., a colour-shape switching task) compared to participants who had their smartphones with them during the study. These studies begin to explore how being separated from one's smartphone affects cognition, which lead to the "brain drain" effect studies by Ward et al. (2017).

Given the way smartphones are used, it is natural to investigate first their potential effects on immediate process. For example, moment to moment attention, or working memory monitoring. Ward et al. found that the mere presence of a participant's smartphone decreased performance on a cognitive task (i.e., a "brain drain" effect). In both experiments, Ward et al. manipulated participant's smartphone location. Each participant's smartphone was placed in one of three locations: (1) on the participant's desk, (2) in their pocket/bag, or (3) outside the testing room. Experiment 1 investigated the effect of people's smartphone on their available cognitive capacity. Participants were randomly assigned to their smartphone location condition and kept their smartphone on silent (i.e., no vibrations if any notifications were received during the study). Those in the "on desk" location conditions were instructed to keep their devices facing down in a specific location. Participants completed two tasks that measured available cognitive capacity: the Automated Operation Span (OSpan) task (Unsworth et al., 2005) and a 10-item subset of Raven's Standard Progressive Matrices (RSPM) test (Raven et al., 1998). They also completed a third task (i.e., the Ending-Digit Drop-Off task), and a measure of smartphone reliance (i.e., the Smartphone Attachment and Dependency Inventory) created for the study.

The OSpan task measured working memory capacity by forcing participants to keep track of task relevant information while engaging in another task. Participants were first presented with the math component of the task: a simple math question (e.g., "(7/7) + 6 = ?") and then indicated whether the correct answer matched a number that was displayed on the next screen (e.g., "7" is "TRUE"). Following the math component, participants were presented with a letter (i.e., the letter component). The math-then-letter component trials were then repeated in blocks. The blocks ranged from a letter string length of three to seven letters, which were randomly displayed. After each block, participants were then asked to recall the letters that were presented between the math questions in order of appearance. Following the recall, participants were given feedback on both math and letter recall performance: they were told how many letters they got in the right order and what percentage of math problems they answered correctly. Only data from those who performed at 85 % math accuracy or higher was used (i.e., to ensure that participants were not ignoring the math component).

The RSPM test was a measure of nonverbal functional fluid intelligence where participants were given an incomplete pattern matrix and selected an element that would best complete the given pattern. The Ending-Digit Drop-Off task measured the tendency to disregard the ending digits of a product's price, which was thought to be more evident in participants whose smartphones were closer to them. After the three tasks, participants in experiment 1 completed a survey measuring their typical smartphone use and some general demographic questions. Reported results showed significantly lower scores for the desk vs. other room conditions on working memory capacity (i.e., OSpan task performance) and for the desk vs. both pocket/ bag and other room conditions on fluid intelligence (i.e., RSPM test performance), but showed no significant effect of location on the Ending-Digit-Drop-Off task (Ward et al., 2017).

Experiment 2 investigated the effect of smartphone presence on cognitive capacity and sustained attention. There were two independent variables: smartphone location (as in experiment 1) and smartphone power. For smartphone power, a participant's smartphone was either: (1) powered ON or (2) powered OFF in their respective location. For all conditions, participants kept their smartphones on silent (i.e., no vibrations if any notifications were received during the study). Also, participants in the "on desk" location conditions were instructed to keep their devices facing up. Participants completed both tasks in counterbalanced order: OSpan task (Unsworth et al., 2005), which was identical to experiment 1; and the Cue-Dependent Go/No-Go task (Bezdjian et al., 2009). The Cue-Dependent Go/No-Go task was a behavioural measure of sustained attention. Participants responded to go targets as fast as possible (i.e., a green rectangle) and withhold a response to no-go targets (i.e., a blue rectangle). Targets were first presented as outlines of rectangles and were either vertical or horizontal. The orientation of the initial target was a cue component, which showed the probability that a given target would be either a go (i.e., 80 % vertical and 20 % horizontal) or no-no target (i.e., 80 % horizontal and 20 % vertical). Once both tasks were completed, participants completed an exploratory survey that measured typical smartphone use and included the Smartphone Attachment and Dependency Inventory (Ward et al., 2017). Results in experiment 2 showed that closer proximity to one's smartphone (i.e., the "on desk" location) was associated with decreased cognitive capacity (i.e., OSpan task performance), but not associated with sustained attention (i.e., Cue-Dependent Go/No-Go task performance). There was no effect of smartphone power on either task. This effect was moderated by smartphone attachment and dependency, where higher smartphone attachment and dependency scores showed a greater “brain drain” effect. Therefore, as in experiment 1, those closer to their smartphone showed impaired OSpan performance and this “brain drain” effect was amplified when participants were more reliant on their smartphone (Ward et al., 2017).

The previous research investigating the “brain drain” effect has focused on the cognitive mechanism of attentional resources. Our smartphone is designed to maintain our attention both while in use (e.g., actively using a smartphone application) and not in use (e.g., anticipating a notification). Ward et al. (2017) supported this cognitive deficit caused by the mere presence of your smartphone. This interference is caused by closer proximity to your smartphone (e.g., on your desk as in Ward et al.) due to the conflict between attending to a task versus your smartphone. It seems that attending to your smartphone is a conditioned response. For example, consider someone who has recently posted on their social media platform using their smartphone which has received many interactions (e.g., comments, shares, likes). If this person is then asked to complete a task which requires them to draw on their attentional or memory resources (e.g., a working memory task as seen in Ward et al.), their resources would be split. That is, the person might be thinking about their smartphone and accessing their social media while completing the task: meaning they are not able to apply all of their cognitive resources to the task. The previous studies force participants into a similar situation, where they are forced to stay away from their smartphone while completing a task. This, as seen by Ward et al. can interfere with their performance and directly relates to their relationship with their smartphone. Why is this so? One possibility is that a smartphone can become a stimulus-response cue (i.e., a social media response cue in the given example). Since the participant is not able to attend to their smartphone and their smartphone might be closer in proximity (i.e., increasing the salience of the smartphone presence), the inanimate object becomes a visual reminder of the function the participant would like to complete (e.g., check their social media). Therefore, attending to the smartphone competes with the cognitive resources needed to complete the task.

The “brain drain” effect of smartphone presence on our cognition was that of the mechanism of attention. Smartphones are designed to capture and retain our attention, so, the closer proximity of one's smartphone interfered with the way you receive and act upon a task. Attending to our smartphone (e.g., thinking about potential notifications) has become a conditioned response (i.e., a stimulus-response association). For example, consider someone who recently posted on a social media platform that has drawn some attention (e.g., comments, replies, shares) who is then required to attend to a different task (e.g., work) and ignore their smartphone. They are not able to use their smartphone but might look toward it or think about when they will be able to check it. In this example, thinking about their smartphone would interfere with their ability to complete the task. This inanimate object becomes a visual reminder of the function they would like to perform (i.e., check the social media post). Attending to their smartphone therefore competes with the task and decreases performance as resources are split between the two processes. This example explores the potential cognitive mechanisms behind Ward et al.'s (2017) original “brain drain” effect, and why replicating this finding is needed to investigate how smartphone presence affect’s cognition.

It should be noted that the literature investigating smartphone presence and cognition has some incongruencies, where recent studies showed supporting (e.g., Tanil & Yong, 2020) and contradicting (e.g., Hartmann et al., 2020) results for Ward et al.'s (2017) findings. Similar findings were seen in Tanil and Yong (2020), where participants either left their smartphone with the experimenter (i.e., away from the participant) or the participant's smartphone was left with the participant. Then, they completed a computerized working memory task span task. Participants recalled either words with increasing length (i.e., pen, refrigerator), letters, or digits (i.e., “1” to “9”). Each stimuli type was used in a separate 25-trial test, where participants were shown the stimuli in sequence, starting at a minimum length, and increasing by one for each correct recall (i.e., in the same order as shown) for a total possible score of 25. Participants who had their smartphone with them showed significantly lower performance. In contrast, Hartmann et al. (2020) found no overall effect of smartphone placement when a participant’s smartphones were either present (i.e., on their desk) or absent (i.e., away from their desk, across the testing room) during a short-term memory and prospective memory task. A moderating effect of smartphone dependency was found for prospective memory, where those with less dependency showed better performance in the absent condition. Overall, there is incongruent evidence for a “brain drain” effect of smartphone presence.

1.2. The present study

The purpose of the present study was to carry out a direct replication of Ward et al.'s (2017) second experiment. Ward et al. found a “brain drain” effect, where closer proximity to one's smartphone impaired working memory capacity (i.e., OSpan performance). This effect was moderated by people's smartphone reliance (i.e., smartphone attachment and dependency score), where higher smartphone reliance resulted in a larger brain drain effect. The evidence provided by experiment 2 in Ward et al. complements previous findings (e.g., Thornton et al., 2014; Wilmer & Chein, 2016) that the mere presence of one's smartphone is enough to affect cognition. Additionally, policy changes such as the Ontario government banning cell phones and smartphones in high schools (Jones, 2019) depict the importance of providing accurate and reproducible data. Therefore, a direct replication of Ward et al.'s (2017) findings will determine whether the brain drain effect is a stable and reproducible effect.

The present study investigated how the mere presence of one's smartphone affects cognition. Based on findings from Ward and colleagues, three main hypotheses were made: a (1) location effect, (2) power effect, and (3) moderation effect. The location effect hypothesis predicted that those who were closest in proximity to their smartphone (i.e., those with their smartphones on their desk) would show lower performance on the OSpan task (Unsworth et al., 2005) but not on the Cue-Dependent Go/No-Go task (Bezdjian et al., 2009). Secondly, the power effect hypothesis predicted that smartphone power (i.e., either ON or OFF) would not affect performance on both cognitive tasks. Lastly, the moderation effect hypothesis predicted that smartphone attachment and dependency would moderate the location effect: those who reported higher smartphone attachment and dependency would have lower OSpan task performance. Replicating Ward et al.'s (2017) findings will not only help to support their original results but will also help guide future studies regarding the influence of smartphones on cognition. Understanding these effects are crucial in a time where smartphones are a basic necessity.

2. Method

The present study was pre-registered as a direct replication of Ward et al.'s (2017) second experiment on Open Science Framework (OSF; Ruiz Pardo et al., 2018). The study's design, hypotheses, and analysis plan followed this OSF registration (https://osf.io/ubys7/).

2.1. Participants

A total of 453 students were recruited from Western University's undergraduate research pool. Of the total sample, 44 participants were excluded due to either testing error (11; e.g., incomplete task data), or experimenter or external confounds (33; e.g., interruption during testing, distracting noise during testing). Only data from participants who scored at 85 % accuracy or above (i.e., including 85 % accuracy) on the math component of the testing session of the OSpan (Unsworth et al., 2005) were used for the final analysis. This is the exclusion criteria from the original task, which helped control for participants who did not follow the math component of the task. For the Cue-Dependent Go/No-Go task (Bezdjian et al., 2009), only data from participants who scored higher than chance performance (i.e., responded to at least 50 % of "Go" trials and withheld response to at least 50 % of "No-Go" trials) were used for the final analysis. Additionally, any participants who had a reaction time (RT) that was higher than two standard deviations from the mean RT were not included in the final analysis. This helped control for any participants who did not follow the task instructions. Therefore, 26 participants were removed during the data cleaning phase, which removed participants who met an exclusion criteria (OSpan math criteria: 20; Go/No-Go response criteria, horizontal/no-go cue: 6; Go/No-Go response criteria, vertical/go cue: 6), were identified as having outlier data (OSpan: 0; Go/No-Go Error Analysis: 0; Go/No-Go RT Analysis: 0), and had incomplete or missing data (OSpan: 3; Go/No-Go Error Analysis: 0; Go/No-Go RT Analysis: 3). Overall, 70 participants were removed from the analysis, where a participant may have been removed due to multiple criteria.

Therefore, a total of 383 students (198 females and 185 males) were used in the present study's analyses. The ages ranged from 17 to 38 years old ($M = 18.87$, $SD = 1.43$). Each participant received a course credit for completing the study. Most participants reported being in their first year of their program (68.67 %; second year = 17.23 %; third year = 7.31 %; fourth year = 4.18 %; did not specify = 2.61 %) and in the Social Science faculty (33.94 %; followed by Science, 23.24 % and Medicine & Dentistry, 18.28 %; see Supplemental Table 1 for more details[1]). Inclusion criteria for the present study was as follows: all participants gave informed consent prior to starting the experiment as university students (i.e., 17 years old or older) and had normal or corrected-to-normal vision (i.e., glasses and contacts were considered corrected and were therefore, acceptable). Participants were also required to have English as their first language or be fluent in English as a second language. The present study was approved through the WREM Ethics Board at Western University.

2.2. Materials

2.2.1. The Automated Operation Span (OSpan) task

The OSpan task (Unsworth et al., 2005) required participants to retain letter strings in memory while solving some simple math problems. This task is a behavioural measure of the attentional control component of working memory. As in Ward et al. (2017), the OSpan task was administered using a computer screen. The present study used a web version of the OSpan task (https://www.millisecond.com/download/library/ospan/), which used the Inquisit 5 software (Inquisit 5, 2016). It was composed of four components which were completed within the same session: three practice components (i.e., letter training, math training, and task training) and one testing component.[2]

The three practice components presented the letter, math, and both the letter and math portions of the final task, respectively. The goal of the practice components was to help familiarize participants with the task to ensure each participant was able to complete the OSpan task. The first practice component trained participants on the letter component of the task, where participants were shown a single letter in the center of the screen and subsequently asked to recall all the letters in the same order. The purpose of the letter training was to allow participants to become familiarized with the letter recall component of the OSpan task. The second practice component trained participants on the math component of the task, where participants were shown a simple math question (e.g., "(7/7) + 6 = ?") and indicated whether an answer was true or false. This component also familiarized participants with their ongoing math performance, which was presented on the screen to encourage them to keep their math performance at 85 % or higher. The third and final practice component trained participants on the full task: a combination of the letter and math components. The purpose of the task training component was to prepare participants for the testing component.

The testing component was the main task. Participants completed 75 blocks identical to the task training blocks (i.e., 75 math problems and 75 letter sets) without any breaks between blocks. The letter sets ranged from three to seven letters in length, which was randomized for each participant. Feedback identical to the task training was given after each block. Once the blocks were completed (i.e., the main task was finished), the following data were presented on the screen: subject number, OSpan absolute score, OSpan total number correct, math total errors, math speed errors, and math accuracy errors. These data were recorded by the experimenter. For more details, please see the "Additional Material and Procedure Description" section of the Supplemental Material.

2.2.2. The Cue-Dependent Go/No-Go task

The Cue-Dependent Go/No-Go task (Bezdjian et al., 2009) measured reaction time (RT) and response accuracy: this task is a behavioural measure of sustained attention. The task was administered on a computer screen using Psychopy (version 1.85.4; Peirce, 2007) and was designed to match the task described in Ward et al. (2017). Participants were presented with the outline of either a vertical or horizontal rectangle that would become filled with either the colour green (i.e., a "go target") or blue (i.e., a "no-go target"). The cue component of the task determined the probability that the rectangle would be either a "go" or "no-go" target. Vertical targets were more likely to become "go" targets (i.e., 80 % "go" and 20 % "no-go"), while horizontal targets were more likely to become "no-go" targets (i.e., 80 % "no-go" and 20 % "go"). Participants were not explicitly made aware of the cue component. Each participant completed a total of 250 trials (50 % "go" trials, 50 % "no-go" trials) without a break between trials. The data recorded from the task was the following: omission errors (i.e., when a participant fails to respond to a "go" target), commission errors (i.e., when a participant responds to a "no-go" target), and a RT measure. For more details, please see the "Additional Material and Procedure Description" section of the Supplemental Material.

[1] A power analysis was completed using G*Power with information from the original findings in Ward et al.'s (2017) second experiment (i.e., for a between-subjects ANOVA, main and interaction effects: $\eta^2_p = 0.026$, number of groups = 6, numerator degrees of freedom = 2, alpha - 0.05, β-1 = 0.81) and resulted in a need for a total sample of 372 (i.e., $n = 62$ per condition). The authors note that the registered sample was not met for the powered on—outside and the powered off—on desk conditions. This was due to the data cleaning process described in the participant section. No additional participants were collected since the new participants would come from an entirely different cohort compared to the original sample which was collected in 2018. The environmental makeup for new participants would be vastly different compared to the original sample since the COVID-19 pandemic has changed the landscape. Therefore, the practicality of adding new participants to the present study is not feasible nor representative of the original sample. This is especially true given the cohort effects described in the discussion section.

[2] It should be noted that the present study used the available version of the OSpan task on Inquisit 5 which matched the OSpan task described in the original Ward et al. (2017) study. However, as no link was given in the Ward et al. study, the authors note that it is possible that the specific components might vary (e.g., practice components) between Ward et al. and the present study.

2.2.3. The demographic questionnaire

The demographic items (i.e., four items in total) in the present study asked participants to report their age (i.e., in years), gender (i.e., male, female, other, or prefer not to say), program (e.g., psychology, engineering), and year of study (e.g., first, fourth). Participants reported their program in an open-ended question and coded into faculties during the data cleaning process. The purpose of these items was to give a brief description of the sample. The demographic questionnaire is shown in Appendix A.

2.2.4. The smartphone use questionnaire

The smartphone use questionnaire was created for the present study and consisted of modified items from Ward et al.'s (2017) exploratory survey measures (i.e., found in the "'BRAIN DRAIN' WEB APPENDIX"). Some items were forced-choice and some were on a 7-point Likert scale ranging from 1 ("Never") to 7 ("Always"). There were 10 items in total and there were three types of items, which measured: (1) smartphone use frequency (three items; e.g., "On average, how many text messages do you send per day?"); (2) smartphone use without external stimulation (two items; e.g., "If I am waiting to meet a friend, I pass the time by using my smartphone."), or during other activities (two items; e.g., "I use my smartphone while driving."); (3) exploratory items, measuring smartphone subjective value (one item; e.g., "How much money would it take for you to give up your phone for a full day?"), smartphone notification type (one item; e.g., "Do you receive notifications (a sound or vibration) on your phone? Please indicate all that apply."), and phantom vibrations (one item; e.g., "Have you ever thought you heard your phone ring or thought you felt it vibrate, only to find out you were wrong?"). The purpose of the smartphone use questionnaire was to measure participants' typical smartphone use. The smartphone use questionnaire is shown in Appendix B.

2.2.5. The smartphone attachment and dependency inventory

The smartphone attachment and dependency inventory (Ward et al., 2017) consisted of 13 items, where participants indicated whether they agreed or disagreed with statements regarding their attachment and dependency to their smartphone. A 7-point Likert scale (ranging from 1, "Strongly Disagree", to 7, "Strongly Agree") was used. Items measured participants' smartphone dependency (e.g., "I feel like I could not live without my cell phone.") and emotional attachment (e.g., "I feel lonely when my cell phone does not ring or vibrate for several hours."). The purpose of the smartphone attachment and dependency inventory was to measure each participant's reliance on their smartphone. The smartphone attachment and dependency inventory items are shown in Appendix C.

2.3. Procedure

Participants completed the study in a semi-grouped lab setting where each participant was seated at their own desk (i.e., with a computer, keyboard, and mouse) with cubicle walls separating each seat. Additionally, participants did not face each other and were separated by approximately two metres or six feet. Up to four participants were tested within the same room at the same time. The experimenter was situated in another room and monitored the study through a two-way mirror.

Participants were randomly assigned to one of six possible conditions. These conditions were based on the two independent variables: smartphone location and smartphone power. For smartphone location, a participant's smartphone was either: (1) on the participant's desk (on desk), (2) in their pocket/bag (pocket/bag), or (3) outside the testing room (outside). For smartphone power, a participant's smartphone was either: (1) powered ON, or (2) powered OFF, in their respective location. Therefore, each participant was in one of six conditions: desk–on (n = 70), pocket/bag–on (n = 67), outside–on (n = 59), desk–off (n = 58), pocket/bag–off (n = 65), and outside–off (n = 64). For all conditions, participants were instructed to keep their smartphones on silent (i.e., no vibrations if any notifications were received during the study). Also, as per Ward et al. (2017), participants in the "on desk" location conditions were instructed to keep their devices facing up.

Once a participant was randomly assigned to their condition, all participants then completed both tasks in counterbalanced order: the OSpan task (Unsworth et al., 2005) and the Cue-Dependent Go/No-Go task (Bezdjian et al., 2009) during one session. The OSpan task took approximately 20 min to complete and the Cue-Dependent Go/No-Go task took approximately 15 min to complete. After completing both tasks, all participants completed the survey measures (approximately 5 min to complete): demographic questionnaire, the smartphone use questionnaire, and the smartphone attachment and dependency inventory (Ward et al., 2017). The entire study took approximately 60 min to complete. For more details, please see the "Additional Material and Procedure Description" section of the Supplemental Material.

2.4. Analyses[3]

2.4.1. The OSpan Task

As in Ward et al. (2017), cognitive capacity was measured by the OSpan (Unsworth et al., 2005): a behavioural measure of the attentional control component of working memory. Performance, measured with the OSpan absolute score, was shown by how many trials a participant correctly recalled all the letters in a given block (75 blocks in total). For example, a participant who recalled three letters (in a block with three letters), five letters (in a block with five letters), and two letters (in a block with six letters) would have an OSpan absolute score of eight for those blocks (i.e., $3 + 5 + 0 = 8$). Since the OSpan absolute score only increased when a participant recalled all letters in a trial correctly, a score of zero was possible. A participant who did recall some letters correctly in any trial, but either incorrectly recalled or missed one or more letters as well would receive a score of zero. Therefore, the OSpan absolute score showed performance where higher scores represented better performance.

2.4.2. The Cue-Dependent Go/No-Go task

As in Ward et al. (2017), sustained attention was measured with the Cue-Dependent Go/No-Go task (Bezdjian et al., 2009). Performance was measured with mean omission errors and RT. It should be noted that mean errors can be divided into total error, commission error, and omission error. Commission errors occurred when a participant responded to a target stimulus. Omission errors occurred when a participant failed to respond to a non-target stimulus. Total errors were the sum of commission and omission errors. The present study focused on mean omission errors. Therefore, for each participant, higher mean omission errors represented lower performance. Additionally, higher mean RT also showed lower performance (i.e., indicative of greater interference).

2.4.3. The smartphone attachment and dependency inventory

Participant's level of smartphone attachment and dependency (i.e., smartphone reliance) was measured with the smartphone attachment and dependency inventory (Ward et al., 2017). The 13-item inventory was scored by calculating a sum total for each item with a range of 13 to 91. Higher scores indicated a higher level of reliance with three levels.

[3] Authors completed an additional set of analyses using Ward et al.'s (2017) original exclusion criteria (i.e., excluding participants who scored <85 % on the OSpan and/or participants who had an average reaction time greater than three times the interquartile range), which resulted a sample total of 385 (i.e., one additional participant in each of the pocket/bag conditions). Results showed no meaningful differences compared to the present study.

3. Results

The present study was pre-registered as a direct replication of Ward et al.'s (2017) second experiment on OSF (https://osf.io/5fq4r) along with a data analysis plan. The final project's data can be found on OSF (https://osf.io/ubys7/).

3.1. Analyses

3.1.1. The OSpan Task

The OSpan absolute score was used. A 3(Smartphone location: desk, pocket/bag, or outside) x 2(Smartphone power: ON or OFF) between-subjects analysis of variance (ANOVA) was conducted. Descriptive statistics are shown in Supplemental Table 2. All analyses assumptions (i.e., independent random sampling, normality, and homogeneity of variance) were met. There was no significant main effect of smartphone location on OSpan performance, $F(2, 377) = 0.10, p = .91, \eta^2_G = 0.001$. There was no significant main effect of smartphone power on OSpan performance, $F(1, 377) = 0.21, p = .65, \eta^2_G = 0.001$. There was also no significant interaction between smartphone location and power on OSpan performance, $F(2, 377) = 1.19, p = .31, \eta^2_G = 0.006$ (Fig. 1). Since there were no significant main or interaction effects, no post-hoc tests were completed.

3.1.2. The Cue-Dependent Go/No-Go task

An error (i.e., omission errors) and RT analysis was completed using the average omission errors and RT for each participant. For the error analysis, a 3 (Smartphone location: desk, pocket/bag, or outside) × 2 (Smartphone power: ON or OFF) × 2 (Cue type: Go or No-Go) mixed factorial design with the between-subjects factors of smartphone location and power, and a within-subjects factor of pre-target cue type was completed. Descriptive statistics are shown in Supplemental Table 2. Since the homogeneity assumption was not met for the mixed ANOVA, a White-corrected F-test was completed for the between-subject effects. There was no significant main effect of smartphone location, $F(2, 377) = 0.67, p = .51, \eta^2_G = 0.002$, and smartphone power, $F(1, 377) = 0.15, p = .70, \eta^2_G = 0.001$. There was a significant main effect of cue type, $F(1, 377) = 23.22, p < .001, \eta^2_G = 0.02$, for average omission errors where the "Go" cue type led to higher average omission errors. Additionally, there was no significant interaction between smartphone location and power, $F(2, 377) = 1.01, p = .37, \eta^2_G = 0.003$, smartphone power and cue type, $F(1, 377) = 0.26, p = .61, \eta^2_G < 0.001$, and between all three factors (i.e., smartphone location, power, and cue type), $F(2, 377) = 0.32, p = .72, \eta^2_G < 0.001$. There was a significant interaction between smartphone location and cue type, $F(2, 377) = 3.19, p = .04, \eta^2_G = 0.005$, however, post-hoc simple main effects for cue type across smartphone location did not show any significant simple main effects for the "go", $F(2, 380) = 1.42, p = .49, \eta^2_G = 0.008$, and "no-go", $F(2, 380) = 0.60, p = .55, \eta^2_G = 0.003$, cue type (see Fig. 2).

For the RT analysis, a 3 (Smartphone location: desk, pocket/bag, or outside) x 2 (Smartphone power: ON or OFF) between-subjects ANOVA was conducted. Descriptive statistics are shown in Supplemental Table 2. All analyses assumptions (i.e., independent random sampling, normality, and homogeneity of variance) were met. There was no significant main effect of smartphone location on average RT, $F(2, 377) = 1.49, p = .77, \eta^2_G = 0.001$. There was no significant main effect of smartphone power on average RT, $F(1, 377) < 0.01, p = .95, \eta^2_G < 0.001$. There was also no significant interaction between smartphone location and power on average RT, $F(2, 377) = 0.04, p = .96, \eta^2_G < 0.001$. Since there were no significant main or interaction effects, no post-hoc tests were completed for the RT analyses (see Fig. 3).

3.1.3. Factor analysis of the smartphone attachment and dependency inventory

As in Ward et al. (2017), responses to the smartphone attachment and dependency inventory were assessed with a factor analysis. A principal axis factor analysis with a Varimax rotation was completed to assess which factors, if any, fit our data and to compare to the two main factors found by Ward et al. (i.e., smartphone dependence and emotional attachment). The results of the factor analysis were also used to form subscale scores for each factor found in the final solution. Factorability of the data was confirmed using: (1) Bartlett's test for correlation adequacy, $\chi^2(78) = 1943.16, p < .001$, which confirmed that correlations between the items were sufficiently large; and (2) the Kaiser-Meyer-Olkin measure for sampling adequacy (MSA), which confirmed that both the overall MSA ($MSA_{overall} = 0.88$) and each item's MSA ($MSA_{1-13} = 0.79$–0.94) were above the required criteria (0.60 and 0.77, respectively; (Kaiser, 1974).

A four-factor solution was chosen for the best fit for the data based on a parallel analysis scree plot, the Kaiser's criterion (i.e., eigen values greater than one), and by comparing the structure for the two-, three-, and four-factor solutions. After an initial four-factor solution was completed using all 13 items in the smartphone attachment and dependency inventory, however, one item was split-loaded between factor

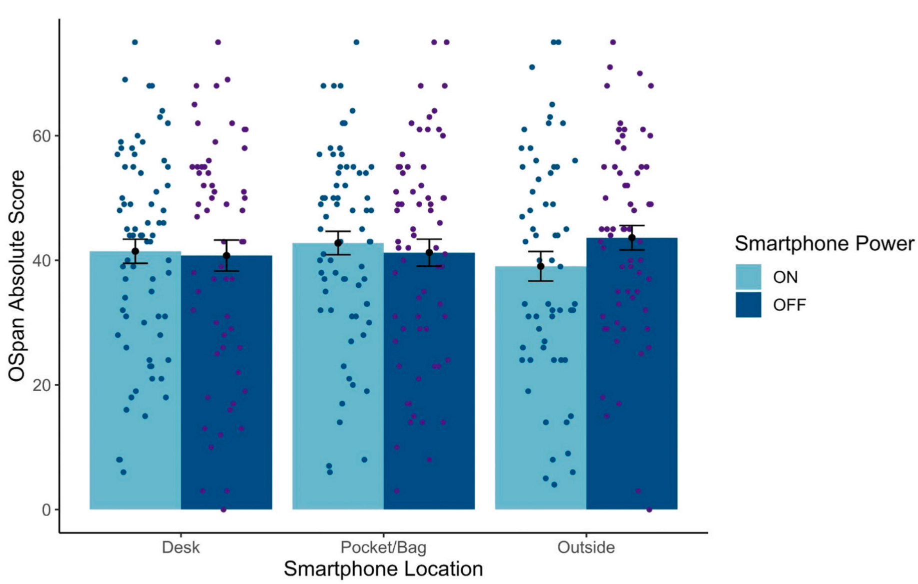

Fig. 1. Comparing operation span performance between smartphone location and power conditions: visual depiction of ANOVA Test.
Note. Plots depict the average performance on the Operation Span (OSpan) Task (i.e., OSpan absolute score; y-axis) for participants across smartphone location (i.e., on desk, left bars; pocket/bag, middle bars; or outside, right bars) and smartphone power (i.e., on, light blue bars; or off, dark blue bars). Black dots and multi-coloured dots represent the mean and individual data points for each condition, respectively. Error bars represent standard error. OSpan absolute score was calculated by summing the total letters recalled for each trial where all letters were recalled correctly; therefore, a score of 0 was possible for any participant who either incorrectly recalled or missed one or more letters in every trial. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

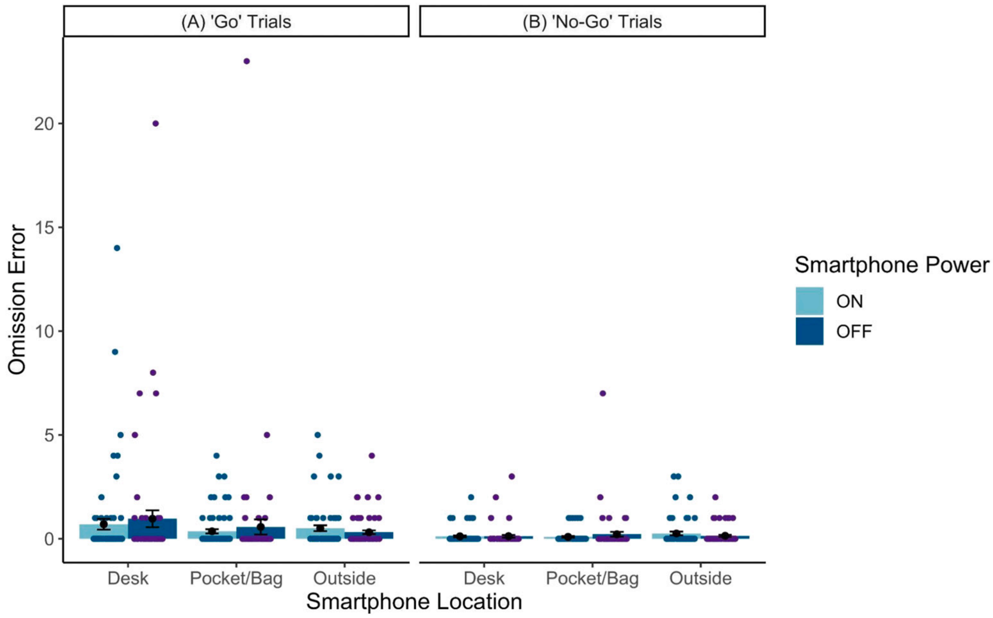

Fig. 2. Comparing Cue-Dependent Go/No-Go omission errors between smartphone location and power conditions by cue type: visual depiction of ANOVA Test.

Note. Plots depict the average performance on the Cue-Dependent Go/No-Go task (i.e., omission errors: responding to a "no-go" target; y-axis) for participants across smartphone location (i.e., on desk, left bars; pocket/bag, middle bars; or outside, right bars) and smartphone power (i.e., on, light blue bars; or off, dark blue bars) by cue type: "go" (A) or "no-go" (B). Black dots and multi-coloured dots represent the mean and individual data points for each condition, respectively. Error bars represent standard error. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

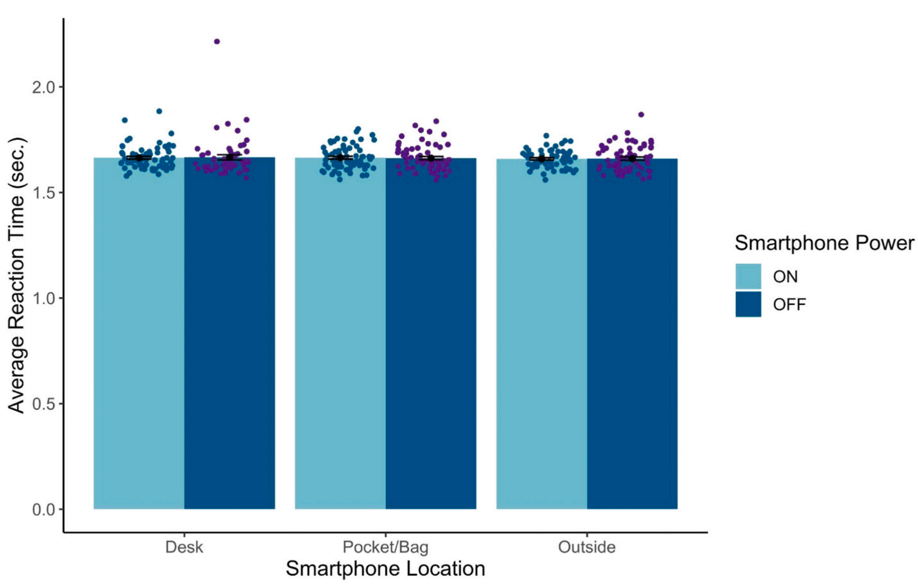

Fig. 3. Comparing Cue-Dependent Go/No-Go average reaction time between smartphone location and power conditions: visual depiction of ANOVA Test.

Note. Plots depict the average performance on the Cue-Dependent Go/No-Go task (i.e., average reaction time in seconds; y-axis) for participants across smartphone location (i.e., on desk, left bars; pocket/bag, middle bars; or outside, right bars) and smartphone power (i.e., on, light blue bars; or off, dark blue bars). Black dots and multi-coloured dots represent the mean and individual data points for each condition, respectively. Error bars represent standard error. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

1 and 3 and was excluded from further analyses (Costello & Osborne, 2005). This final solution achieved simple structure and was used for subsequent analyses. The final solution showed a good fit (Root Mean Square of the Residual = 0.03).

The final solution's factors explained 52.97 % of the variance and suggested the following three factors: dependence, emotional attachment, accessibility, and distractibility (see Table 1). Dependence was related to the degree of dependence on one's smartphone, it consisted of 3 items and explained 16.68 % of the variance. Emotional attachment was related to one's smartphone use for emotional support, it consisted of 4 items and explained 15.48 % of the variance. Accessibility was related to the ability to access the utility of one's phone (e.g., powered on, internet access), it consisted of 3 items and explained 11.84 % of the variance. Distractibility was related to one's smartphone retaining one's attention, it consisted of two items and explained 8.97 % of the variance. All three factors had moderate reliability, measured with Cronbach's alpha ($\alpha_{Dep.} = 0.83$, $\alpha_{EA} = 0.76$, $\alpha_{Access} = 0.72$, $\alpha_{Dist} = 0.63$; Kline, 1999). No increases were seen in Cronbach's alpha by eliminating more items for any of the factors. A composite sum-score was created for each factor, where higher scores indicated higher dependency (possible range = 3–21; $M = 12.63$, $SD = 4.73$), emotional attachment (possible range = 4–28; $M = 16.73$, $SD = 4.91$), accessibility (possible range = 3–21; $M = 9.98$, $SD = 2.70$), and distractibility (possible range = 2–14; $M = 6.25$, $SD = 1.03$), respectively. Additional descriptive statistics for the four factors are shown in Supplemental Table 3.

3.1.4. Moderation analysis on OSpan Score

The present study's findings partially supported Ward et al.'s (2017) findings and provided the groundwork for the moderator analysis. In support of Ward et al.'s findings, the present study found no effect of power on either task performance and there was no meaningful effect of smartphone presence on Cue-Dependent Go/No-Go task (i.e., a main effect of cue type but no significant simple main effect on average omission error). Contrary to Ward et al. there was no support for the effect of smartphone presence on OSpan task performance. To examine if smartphone dependency, emotional attachment, accessibility, or

Table 1
Summary of exploratory factor analysis of the 13 items in the smartphone attachment and dependency inventory from Ward et al. (2017).

		Rotated Factor Loadings						
Item	Description	1	(*)	2	(*)	3	(*)	4
Factor 1: Dependency								
1	I would have trouble getting through a normal day without my smartphone.	**0.72**	(0.85)	0.21		0.24		0.12
2	It would be painful for me to give up my smartphone for a day.	**0.82**	(0.81)	0.28		0.19		0.05
3	I feel like I could not live without my smartphone.	**0.61**	(0.79)	0.18		0.24		0.17
Factor 2: Emotional Attachment								
8	I feel lonely when my smartphone does not ring or vibrate for several hours.	0.18		**0.44**	(0.73)	0.32		0.19
9	Using my smartphone relieves me of my stress.	0.24		**0.58**	(0.71)	0.20		0.09
10	I feel excited when I have a new message or notification.	0.10		**0.73**	(0.70)	0.21		0.13
11	Using my smartphone makes me feel happy.	0.30		**0.67**	(0.68)	0.09		0.11
Factor 3: Accessibility								
5	It drives me crazy when my smartphone runs out of battery.	0.37	(0.66)	0.20		**0.56**		0.14
6	I am upset and annoyed when I find I do not have reception on my smartphone.	0.26	(0.64)	0.21		**0.68**		0.19
7	I feel impatient when the Internet connection speed on my smartphone is slow.	0.15	(0.52)	0.25		**0.48**	(0.43)	0.21
Factor 4: Distractibility								
12	I find it tough to focus whenever my smartphone is nearby.	0.15		0.18	(0.64)	0.09		**0.67**
13	I become less attentive to my surroundings when I'm using my smartphone.	0.06		0.08		0.24	(0.90)	**0.63**
Eigen Values		2.00		1.89		1.42		1.08
Percent of Variance Explained (*)		16.68	(31.02)	15.48	(21.65)	11.84		8.97
α(*)		0.83	(0.89)	0.76	(0.79)	0.72		0.63

Note: Items have been sorted based on rotated (varimax) factor loading. Strongly loaded items for present study (>0.40) are shown in bold font. Item four was removed due to split-loading between factors 1 (0.58) and 2 (0.41): "I am upset and annoyed when I find I do not have reception on my smartphone.". This loading was 0.75 in Ward et al. (2017).
* Values given in Ward et al. (2017). Only two strong factors (smartphone dependency and emotional attachment) were included with respective strong loadings. $N = 383$.

distractibility were moderators of the relationship between the experimental manipulation and OSpan performance, a pre-registered analysis using a univariate generalized linear model was used. As in Ward et al. (2017), OSpan performance was the criterion, smartphone location (i.e., desk, pocket/bag, and outside) was the independent variable, and the following were used as possible predictors, each in a separate analyses: the mean-centered dependency, emotional attachment, accessibility, and distractibility composite score. Additionally, all independent variable x moderator interaction terms were included as predictors in the model (Baron & Kenny, 1986). Therefore, each regression model had the following predictors for the criterion (i.e., OSpan absolute score): (1) moderator, (2) smartphone location comparisons (i.e., desk vs. pocket/bag, desk vs. outside, and outside vs. pocket/bag), and (3) all interaction between (1) and (2). Outliers were removed if participants fell outside of

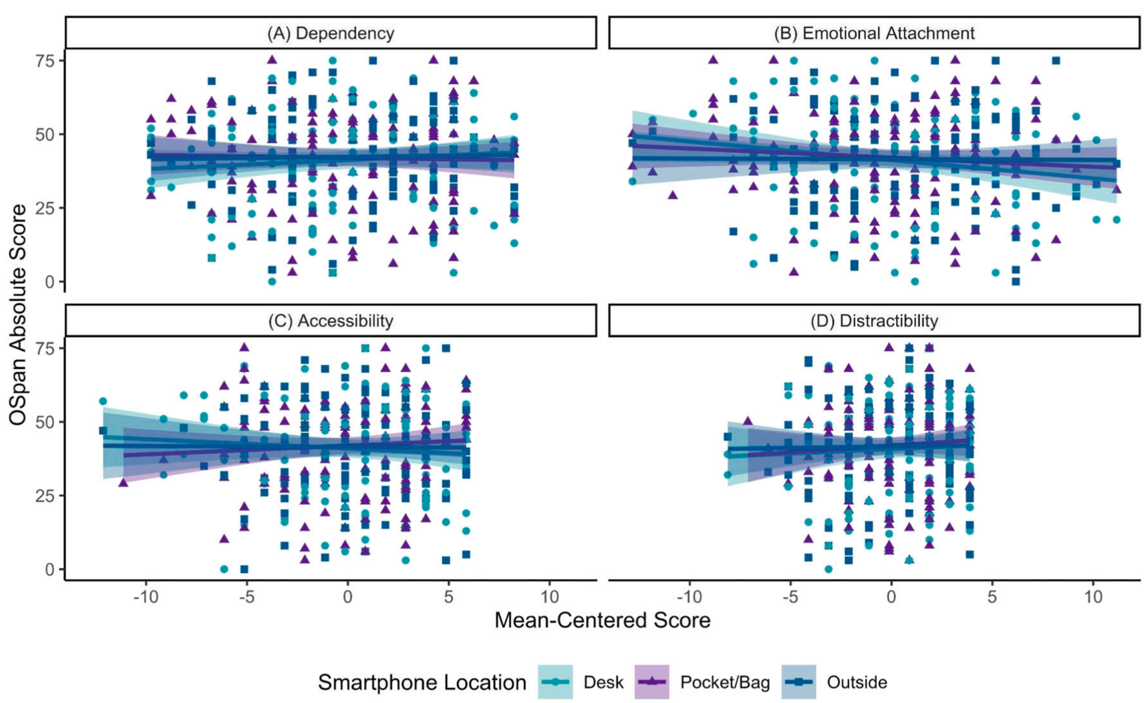

Fig. 4. Moderation analyses of operation span performance for each subscale in the smartphone attachment and dependency inventory grouped by smartphone location: visual depiction of moderation models.
Note. Plots depict the average performance on the Operation Span (OSpan) Task (i.e., OSpan absolute score; y-axis) vs. the mean-centered score (x-axis) for Dependency (A), Emotional Attachment (B), Accessibility (C), and Distractibility (D) across the smartphone location conditions (i.e., on desk, light blue; pocket/bag, purple; or outside, dark blue). Shaded region depicts the 95 % confidence interval. Individual data points are shown for each condition, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

both the Leverage and Cook's criteria, which resulted in differing samples for dependency ($N = 376$), emotional attachment ($N = 379$), accessibility ($N = 377$), and distractibility ($N = 375$). For all models, the assumptions of multicollinearity, linearity, normality, and homogeneity were met.

3.1.4.1. Smartphone dependency. The overall model predicting OSpan performance using smartphone location and dependency score was not significant, $F(5, 370) = 0.31$, $p = .91$, $R^2 = 0.004$. Dependency, $p = .30$, smartphone location, $p > .62$, and the dependency x smartphone location interactions, $p > .36$, were not significant predictors of OSpan absolute score (see Supplemental Table 4 A for more details). A visual inspection of the model did not show any trends (Fig. 4A).

3.1.4.2. Smartphone emotional attachment. The overall model predicting OSpan performance using smartphone location and emotional attachment score was not significant, $F(5, 373) = 1.05$, $p = .39$, $R^2 = 0.01$. Emotional attachment approached a significant predictor of OSpan performance, $p = .05$. Smartphone location, $p > .70$, and emotional attachment x smartphone location interactions, $p > .18$, were not significant predictors of OSpan absolute score (see Supplemental Table 4B for more details). A visual inspection of the data showed a trend in the desk condition, where participants who reported lower smartphone emotional attachment showed higher OSpan performance. This trend was weaker in the outside condition and not seen in the pocket/bag condition (Fig. 4B).

3.1.4.3. Smartphone accessibility. The overall model predicting OSpan performance using smartphone location and accessibility score was not significant, $F(5, 371) = 0.27$, $p = .93$, $R^2 = 0.004$. Accessibility, $p = .42$, smartphone location, $p > .63$, and moderator x smartphone location interactions, $p > .29$, were not significant predictors of OSpan absolute score (see Supplemental Table 4C for more details). A visual inspection of the model did not show any trends (Fig. 4C).

3.1.4.4. Smartphone distractibility. The overall model predicting OSpan performance using smartphone location and distractibility score was not significant, $F(5, 369) = 0.23$, $p = .95$, $R^2 = 0.003$. Distractibility, $p = .59$, smartphone location, $p > .57$, and moderator x smartphone location interactions, $p > .67$, were not significant predictors of OSpan absolute score (see Supplemental Table 4D for more details). A visual inspection of the model did not show any trends (Fig. 4D).

3.1.5. The smartphone use questionnaire

Smartphone use frequency was measured with respect to average daily text messages sent, social media based messages sent, and social media posts. Most participants reported sending >15 text messages (60.31 %), >15 social media based messages (64.23 %), and only zero to five social media based posts (80.94 %) per day. Average smartphone use without external stimulation ($M = 6.25$, $SD = 1.03$) was higher than use during other activities ($M = 2.73$, $SD = 1.22$). Smartphone subjective value showed that most people reported willingness to go without their phone for a day for only $0–$20 (36.55 %). With respect to smartphone notification type, out of all the notifications participants reported receiving (1256 total), Snapchat (23.33 %) was the application they most receive a sound or vibration notification on their phone (followed by Email, 22.05 %; Instagram, 19.27 %; and, Facebook, 18.23 %, respectively). Finally, most participants (86.42 %) reported they had felt a phantom vibration (i.e., perceiving they received a notification on their phone, when in fact there was no notification) in the past (see Supplemental Table 5 for more details).

4. Discussion

Smartphones provide an easy and effective method of communicating with the world right at our fingertips. The rising prevalence of smartphones (Pew Research Center, 2019) has prompted research including possible behavioural addictions (WHO, 2015) and how these might affect cognitive abilities. Although there are many benefits to using a smartphone in terms of communication, the present study investigated how smartphones affect performance on cognitively demanding tasks. This was done by reexamining the "brain drain" effect (i.e., those who were in closer proximity to their smartphone performed worse on a cognitively demanding task, which is moderated by smartphone reliance) found by Ward et al.'s (2017) second experiment. The three main hypotheses (i.e., location effect, power effect, and moderation effect) from Ward et al. (2017) were evaluated in the present study.

4.1. The OSpan Task and the Cue-Dependent Go/No-Go task

There were no significant main or interaction effects of smartphone location on performance on OSpan absolute score. There was a significant main effect of cue type and an interaction effect of cue type and smartphone location on omission errors in the Cue-Dependent Go/No-Go task (Bezdjian et al., 2009). However, this effect was explored with tests of simple main effects and found no significant effect of smartphone location for either cue type. Overall, the present study did replicate Ward et al.'s null effect on the Cue-Dependent Go/No-Go task performance. More notably, however, the present study's findings failed to replicate Ward et al.'s main effect concerning performance on the OSpan task (Unsworth et al., 2005). Therefore, the "brain drain" effect was not replicated in the present study. The smartphone power effect hypothesis was supported: there was no significant difference between power conditions (i.e., powered ON vs. OFF) on performance for both tasks. This was a replication of Ward et al.'s findings.

4.2. Factor analysis of the smartphone attachment and dependency inventory

Findings from a principal components analysis on the smartphone attachment and dependency inventory (Ward et al., 2017) partially supported the two-factor findings from Ward et al. (i.e., smartphone dependence and emotional attachment), but also added a third factor: smartphone distractibility.

4.3. Moderation analysis on OSpan Score

Finally, the moderation effect did not replicate: smartphone dependency, emotional attachment, and distractibility were not significant moderators of OSpan performance. In contrast with Ward and colleagues, emotional attachment showed a trend for those in the desk condition, where higher emotional attachment predicted lower OSpan performance. It should be noted that this analysis was completed as a pre-registered analysis and was exploratory in nature. Overall, the present study demonstrated that the "brain drain" effect may not be a replicable effect of smartphone presence on cognition. Possible reasons for this are given.

4.4. Failure to replicate the "brain drain" effect

A stark difference in performance was observed between the present study's OSpan performance and in Ward et al.'s (2017) second experiment. This was one of the critical results in Ward et al., because they described the OSpan as a difficult working memory task intended to be sensitive to a decrease in cognitive capacity. They argued that this difficulty difference was the reason why they found an effect on OSpan performance but not on the Cue-Dependent Go/No-Go (Bezdjian et al., 2009) performance, and indeed this was the locus of the "brain drain" effect. However, participants in our study did not find the OSpan as challenging and the presence of their own smartphone on the desk did not seem to interfere with their performance on the task. Not only was the mean-difference in OSpan performance for the present study much smaller than for Ward et al. but also, the average performance between the present study and Ward et al. implies that participants in the present study did not find the OSpan task as challenging as in Ward et al.'s study. This difference was also seen when compared to Ward et al.'s first experiment, where average OSpan performance was lower than a score of 34. These differences may explain why participants in our experiment did not experience a “brain drain” in their performance: the task did not diminish participant's available cognitive capacity. In fact, the present study showed participants with perfect performance on both the math and letter recall components and, consequently, there was a possible ceiling effect. This defeated the purpose of the OSpan as a more difficult cognitive task. Therefore, to determine the underlying mechanisms behind smartphones' impact on cognition, future work should use reliable and normed cognitive tasks. The Cambridge Brain Sciences (CBS; Hampshire et al., 2012) test battery, for example, evaluates a broad range of cognitive abilities such as selective attention, response inhibition, reasoning, and working memory. These short cognitive tests have been used across different populations (Wild et al., 2018) to test people across three main components (i.e., short-term memory, reasoning, and verbal ability) with varying difficulty levels. Therefore, using this test battery could examine how smartphone presence affects an overview of cognitive aspects and could explain why the present study did not replicate the “brain drain” effect.

Another limitation to consider in the present study was the measure for smartphone reliance. In order to directly compare the present study to Ward et al.'s second experiment, the smartphone attachment and dependency inventory (Ward et al., 2017) was used to measure participant's smartphone attachment and dependency (i.e., reliance). However, current research typically uses additional measures to measure things such as nomophobia (i.e., the fear of being without one's phone or the internet; (Yildirim & Correia, 2015) and smartphone involvement (Walsh et al., 2010). Although the use of the smartphone attachment and dependency inventory (Ward et al., 2017) allowed the present study to directly compare findings to Ward et al.'s second experiment, measuring smartphone reliance based on only one scale limited the present study. Therefore, future research should expand on other measures of smartphone reliance.

Additionally, it should be noted that the present study focused on a North American population to compare directly to Ward et al.'s original study. However, as smartphone prevalence emerges globally and differently across countries (Silver, 2019), future research should consider comparing different countries' smartphone use.

5. Conclusion

The present study reexamined the “brain drain” effect found in Ward et al.'s (2017) second experiment. The “brain drain” effect found that those who were in closer proximity with their smartphones (i.e., those with their smartphones on their desk during the task) performed worse on a cognitively demanding task (i.e., the OSpan). In order to investigate this effect, the materials, methods, and analyses were completed based on the original study (all of which was pre-registered through OSF; Ruiz Pardo et al., 2018). Although some findings were replicated (e.g., the non-significant effect of smartphone power, the partial support for the same factors in the smartphone attachment and dependency inventory), the main “brain drain” effect was not replicated in the present study. This is an important finding because it presents an interesting new question in the field: what effect can smartphone presence, if any, have on cognition? It is possible that the mere presence of one's smartphone is not the cause of a cognitive deficit. Some possible reasons include individual differences (e.g., gender, age, personality differences) or simply the task used to investigate the effect. The continued increase in global smartphone ubiquity (Pew Research Center, 2019) makes this gap in the field relevant to every-day life. Finding and understanding these possible impacts remains critical to deciphering how smartphones may impact cognition and provide scientific evidence for means to help thwart these effects.

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Declaration of competing interest

None declared.

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Ethical considerations & disclosure

Study was conducted in accordance with ethics protocols approved by Western University's Non-Medical Research Ethics Board (#110296).

Appendix A. Demographic questionnaire

GENERAL DEMOGRAPHICS

1. What is your gender?
   a. Male
   b. Female
   c. Other (please specify) ____________
   d. Prefer not to say
2. Age (in years): ___________
3. Program: ___________
4. Year of Study: ___________
5. Is your first language English?
   a. Yes
   b. No

Appendix B. Smartphone use questionnaire

SMARTPHONE USE FREQUENCY

1. On average, how many **text messages** do you send **per day**?
   a. 0–5
   b. 6–10
   c. 11–15
   d. >15
2. On average, how many **social media based messages** do you send **per day** from your smartphone? (iMessage, Facebook Messenger, WhatsApp, WeChat, direct messages within social media platforms, etc.)
   a. 0–5
   b. 6–10
   c. 11–15
   d. >15
3. On average, how many **social media posts** (e.g., written post, picture, article, etc.) do you send **per day** from your smartphone? (Facebook, Twitter, Instagram, etc.)
   a. 0–5
   b. 6–10
   c. 11–15
   d. >15

SMARTPHONE USE WITH EXTERNAL STIMULATION OR DURING OTHER ACTIVITIES
For the following questions, please indicate how often the following statements apply to you.

Never			Neutral			Always
1	2	3	4	5	6	7

Tendency to turn to one's smartphone in the absence of external stimulation:

1. I look at my smartphone before I roll out of bed in the morning.
2. If I am waiting to meet a friend, I pass the time by using my smartphone.

Tendency to turn to one's smartphone in the midst of other activities:

3. I use my smartphone while driving.
4. If my smartphone rings or vibrates in the middle of personal business, I look at it.

EXPLORATORY ITEMS
Smartphone subjective value:

1. How much money would it take for you to give up your phone for a full day?
   a. $0–$20
   b. $21–$40
   c. $41–$60
   d. >$60

Types of smartphone notifications:

2. Do you receive notifications (a sound or vibration) on your phone? Please indicate all that apply.

☐ Email	☐ Twitter	☐ LinkedIn	☐ Other (please specify) __________
☐ Facebook	☐ Instagram	☐ Snapchat	

Phantom vibration experiences:

3. Have you ever thought you heard your phone ring or thought you felt it vibrate, only to find out you were wrong?
   a. Yes
   b. No

Appendix C. Smartphone attachment and dependency inventory

Source: Ward et al. (2017)

For the following questions, please indicate how much you agree or disagree to the following statements.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
1	2	3	4	5	6	7

1. I would have trouble getting through a normal day without my smartphone.
2. It would be painful for me to give up my smartphone for a day.
3. I feel like I could not live without my smartphone.
4. If I forgot to bring my smartphone with me, I would feel anxious.
5. It drives me crazy when my smartphone runs out of battery.
6. I am upset and annoyed when I find I do not have reception on my smartphone.
7. I feel impatient when the Internet connection speed on my smartphone is slow.
8. I feel lonely when my smartphone does not ring or vibrate for several hours.
9. Using my smartphone relieves me of my stress.
10. I feel excited when I have a new message or notification.
11. Using my smartphone makes me feel happy.
12. I find it tough to focus whenever my smartphone is nearby.
13. I become less attentive to my surroundings when I'm using my smartphone.

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.actpsy.2022.103717.

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