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Attentional bias towards smartphone stimuli is associated with decreased interoceptive awareness and increased physiological reactivity

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Excessive smartphone use has been linked to negative psychological outcomes and may also be associated with cognitive impairments and disruptions in mind-body interaction, though the underlying mechanisms remain unclear. Here, we investigated attentional bias towards marginal smartphone stimuli and its relationship with interoceptive awareness and physiological cue reactivity in healthy young adults. Fifty-eight participants completed a letter detection task with varying perceptual loads, during which task-irrelevant smartphone-related or scrambled images were presented in the background. Cardiac responses were recorded to assess physiological reactivity. Participants also completed two questionnaires for interoceptive awareness and self-report smartphone addiction. Using a designed and automated clustering based on behavioural responses, participants were classified into two groups: one group exhibited distraction from smartphone background only under low perceptual load, while the other showed consistent attentional bias regardless of load. Notably, the latter group reported significantly lower interoceptive awareness and higher smartphone addiction scores. Additionally, they exhibited heart rate acceleration in response to smartphone stimuli, indicating heightened arousal, whereas the former group showed heart rate deceleration. These findings demonstrate that consistent attentional bias towards smartphone stimuli is associated with reduced interoceptive awareness, specifically a decreased tendency to notice and trust internal bodily sensations, and increased physiological reactivity.

The widespread use of smartphones has raised concerns about their potential effects on cognitive functions. Excessive smartphone use is characterised by compulsive and maladaptive behaviours that interfere with daily life, including work, relationships, and physical health[1], while debates continue over whether such conditions constitute a behavioural addiction[2–4]. Despite the controversy, researchers have considered shared features with behavioural addictions in excessive smartphone use, including withdrawal-like behaviours and tolerance-like behaviours[5–7]. Additionally, negative psychological outcomes, such as increased anxiety and decreased well-being, have been reported in such conditions[8,9]. However, the fundamental cognitive and physiological mechanisms underlying excessive smartphone use remain insufficiently examined. In this study, we investigate attentional biases and physiological responses triggered by smartphone-related stimuli in a healthy young adults population.

Attentional bias and physiological cue reactivity are core features of addictive behaviours, involving automatic responses to addiction-related cues. Attentional bias denotes preferential attention to such stimuli, reinforcing their prominence and perpetuating the addiction cycle[10–12]. Cue reactivity refers to heightened physiological and psychological responses, often leading to cravings or urges[13,14]. Preliminary evidence suggests that excessive smartphone users exhibit neural and behavioural patterns similar to those seen in other addictions. For example, they exhibit altered brain activity in inhibitory systems and reduced attentional control against smartphone-related stimuli, compared with healthy controls[15–18]. However, it has also been suggested that smartphone stimuli capture attention in the

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general population[19–22], raising the question of whether these biases reflect addiction processes or broader attentional phenomena specific to modern technology use. It is therefore necessary to investigate attentional bias and cue reactivity to smartphone stimuli and their relationship with individual dispositions, to elucidate whether these responses reflect behavioural addiction-like mechanisms.

Interoceptive awareness—the conscious perception of internal bodily signals—has emerged as a significant factor in understanding addictive behaviours. It has been proposed that interoceptive dysfunctions may contribute to the development and maintenance of addiction cycles, particularly through its influence on reward processing and emotional regulation[23–25]. Following this, recent studies have reported reduced interoceptive awareness assessed via questionnaires in individuals with behavioural addictions, including alcohol dependence, gambling disorder, and problematic internet use[26,27]. In excessive smartphone users, reduced grey matter volume in the insula—a key region for both interoceptive awareness and substance use[28], has been observed, suggesting a link between smartphone use, interoception, and behavioural addictions[29]. Additionally, mindfulness-based interventions designed to improve interoceptive awareness have shown effectiveness in reducing problematic smartphone use[30,31]. Despite these insights, the relationship between attentional biases towards smartphone stimuli and interoceptive awareness has not been directly examined so far.

To address these gaps, this study investigates attentional bias towards smartphone stimuli and its relationship with cue reactivity and interoceptive awareness in healthy young adults. Participants performed a letter detection task, identifying target letters while ignoring task-irrelevant background images featuring smartphone-related or scrambled pictures. Concurrently, we recorded participants' cardiac responses to the distracting backgrounds using electrocardiography (ECG) as a measure of physiological cue reactivity. We manipulated task difficulty and background stimuli on a trial-by-trial basis to assess attentional bias at the individual level[32]. Unlike previous studies that primarily employed spatial attention paradigms such as the dot-probe task[21], our design allows for a more detailed examination of attentional processes involving information conflict and selective processing. Importantly, we did not pre-classify participants based on self-reported smartphone use. Instead, we grouped participants post hoc based on their behavioural responses during the task and then compared measures of interoceptive awareness, smartphone addiction scale, and physiological cue reactivity between these subgroups. This approach allows us to explore attentional bias to smartphone stimuli and its connection to interoceptive awareness without presuming that excessive smartphone use is inherently pathological.

We hypothesised that individuals who exhibit stronger attentional bias towards smartphone stimuli will display decreased interoceptive awareness, heightened physiological responses to smartphone cues, and higher levels of self-report smartphone use, drawing parallels with attentional patterns observed in other behavioural addictions[11,14]. By elucidating the relationships between attentional bias, physiological responses, and smartphone use, this study aims to enhance understanding of the cognitive and physiological mechanisms associated with smartphone-related attentional biases.

Methods

Participants

Based on a preliminary analysis, we conducted a power analysis using G*Power 3.1. With an effect size of $d = 0.80$, $\alpha = 0.05$, and 80% power, the required sample size was determined to be 54. This analysis accounted for the approximate 1:2 ratio of group occurrence in the preliminary sample (consistent attentional bias vs. non-consistent bias). We analysed data from 58 participants, recruited via the Sona System at Centre for Experimental Research in Social Sciences (CERSS), Hokkaido University. Participants were Japanese young adults (30 women, 28 men; mean age = 19.59 years, SD = 1.34 years), who completed a 60-minute experimental session and received a 1,500-yen Amazon gift card as compensation. Additional forms of payment, such as extra monetary rewards or course credit, were not provided. No data was excluded based on the individual level of smartphone addiction. Written informed consent was obtained from all participants prior to the start of the study. At the same time, we collected gender information of each participant, while the race or ethnicity was not assessed. The study was conducted according to the Declaration of Helsinki and its amendments and was approved by the Ethics Committee of CERSS, Hokkaido University.

Apparatus

The experiment was conducted using a Windows computer connected to a stimulus-presentation monitor (1920 × 1080 resolution, 60 Hz refresh rate) and a keyboard for recording responses. Participants were seated in front of the desk and the distance was kept approximately 50 cm from the monitor throughout the experiment. They placed their left index finger on 'x' and right index finger on 'n' keys. During the whole experiment, an ECG was recorded using an Arduino-based device (ArdMob-ECG)[33] with a sampling rate of 1000 Hz. A three-electrode setup in a modified Lead II configuration with Ag/AgCl electrodes was employed. One electrode was placed below the right clavicle, one below the left clavicle, and the third at the lower left rib area to ensure stable R-wave detection and consistent heart rate measurement. QRS complexes were detected in real-time using a simplified Pan-Tompkins algorithm, and the experiment commenced only after verifying stable ECG signals.

Letter detection task

We employed a letter detection task to investigate the impact of smartphone-related images on attentional capture under varying perceptual load conditions[32]. The task was designed to examine how task-irrelevant smartphone images affect the ability to identify target letters and how this effect is modulated by the difficulty of the central task.

The experiment utilised a 2 × 2 within-subjects design, manipulating perceptual load (low, high) and distractor type (smartphone, scrambled). Participants completed 200 trials in total, with 50 trials per condition. The low-load condition was designed to minimise cognitive demand, presenting six repetitions of the target letter (e.g., 'XXXXXX'), thereby allowing greater susceptibility to distraction. In contrast, the high-load condition, which required identifying a target letter embedded among five randomly selected non-target letters (e.g., 'AKXTRF'), imposed greater cognitive demand, reducing the attentional resources available for processing irrelevant stimuli. This manipulation aligns with the load theory of attention, which posits that increased perceptual load limits the processing of task-irrelevant stimuli and reduces susceptibility to distraction[34]. The background images were either smartphone-related (smartphone condition) or scrambled versions of these images (control condition), with five distinct images used for each category. The smartphone-related stimuli were all illustrations, depicted with the screen turned on. Three images showed a home screen, one featured an incoming call screen, and another displayed a chat screen. These images were selected and processed from free-license sources (https://www.ac-illust.com/). To prevent unnecessary allocation of attention resources, no text or numbers were included on any of the screens. The scrambled images were created by randomly rearranging each image at the pixel level, preserving the same features like colour distribution or figure size as the original images. The characteristics of the images, such as familiarity, arousal, or dominance ratings were not collected prior to experiment.

Each trial began with a fixation cross displayed for 3500–5500 ms (mean = 4500 ms), followed by a 200 ms presentation of the letter string superimposed on the image. The background image, which was either a smartphone-related or scrambled image, was presented at a size of 600 pixels in width and 1020 pixels in height, covering a significant portion of the screen. Participants were instructed to identify the target letter as quickly and accurately as possible by pressing the corresponding key, while ignoring the background images (Fig. 1A). The correctness of each response, reaction time (RT), and timing of heartbeat occurrence were recorded for each trial. The experiment was divided into four blocks of 50 trials each, with rest

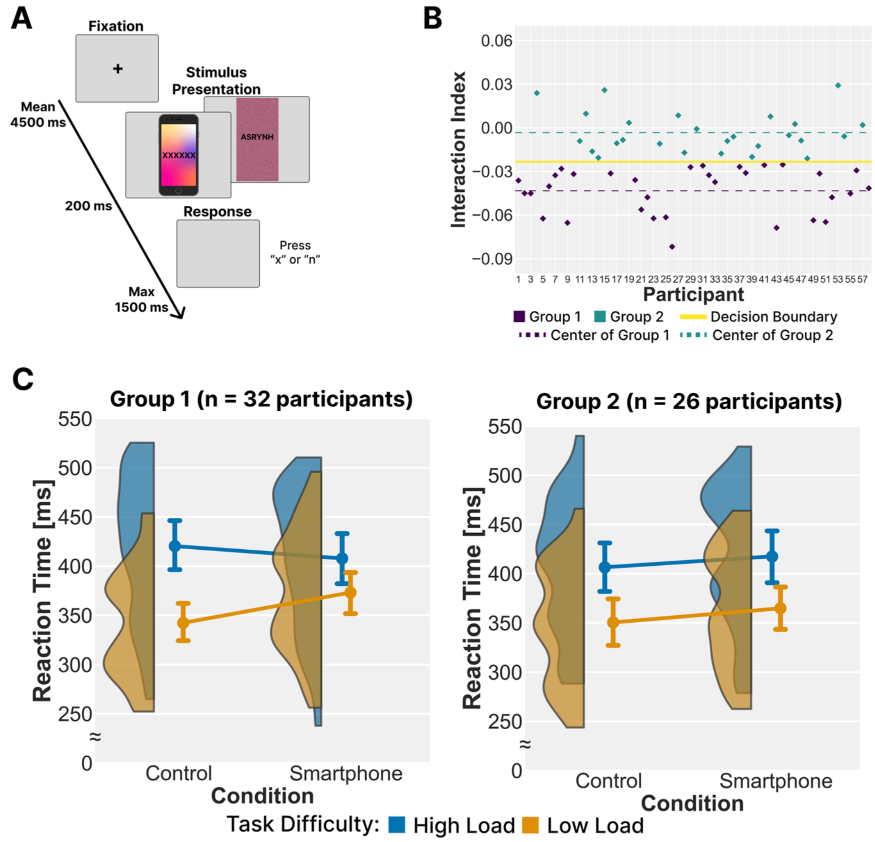

Fig. 1 | Experimental design and classification of participants based on attentional bias to smartphone stimuli under varying cognitive load. **A** Task paradigm. Participants fixated on a cross for a mean duration of 4500 ms, followed by a stimulus presentation for 200 ms. Stimuli consisted of either a smartphone screen (Smartphone condition) or a scrambled control image (Control condition) overlaid with a string of letters. Participants responded by pressing 'x' or 'n' to indicate whether the letters matched a target string, with a maximum response time of 1500 ms. **B** Participant classification using K-means clustering (K = 2) based on the interaction index between condition (Smartphone vs. Control) and task difficulty (High vs. Low Load). Group 1 (purple) consists of participants who showed a greater distraction effect in low-load conditions, indicated by a negative interaction index, while Group 2 (teal) comprises participants with a consistent attentional bias towards smartphone stimuli, showing positive or near-zero interaction index values. The centres for each group are shown as dashed lines, and the decision boundary (yellow) separates the groups. **C** Reaction times (RTs) for Group 1 (left) and Group 2 (right) across conditions (Control and Smartphone) and task difficulties (High Load and Low Load). In Group 1, RTs were slower in the Smartphone condition during the low-load task, but this effect reversed in the high-load task, showing a significant interaction effect between condition and difficulty. In contrast, Group 2 exhibited slower RTs in the Smartphone condition regardless of task difficulty, indicating a consistent attentional bias towards smartphone stimuli. Error bars represent standard errors of the mean.

periods between blocks. Participants could take breaks as needed. The order of trials was randomised for each participant to control for order effects. A warning message ('Please respond faster!') appeared if participants failed to respond within 1500 ms, ensuring sustained attention throughout the experiment.

Questionnaires

To assess individual differences in smartphone addiction and interoceptive awareness, participants completed self-report questionnaires. All questionnaires were administered in Japanese using translations of the original instruments. The Smartphone Addiction Scale-Short Version (SAS-SV)[6] was used to measure participants' level of smartphone addiction. This 10-item scale assesses various aspects of problematic smartphone use, including daily-life disturbance, positive anticipation, withdrawal, cyberspace-oriented relationships, overuse, and tolerance. Items are rated on a 6-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree), with higher scores indicating a greater degree of smartphone addiction.

Interoceptive awareness was assessed using the Multidimensional Assessment of Interoceptive Awareness (MAIA)[35]. The MAIA is a 32-item instrument that measures eight dimensions of interoception: noticing, not-distracting, not-worrying, attention regulation, emotional awareness, self-regulation, body listening, and trusting. Participants responded to each item on a 6-point Likert scale from 0 (never) to 5 (always), with higher scores indicating greater interoceptive awareness in each dimension.

To minimise order effects and potential biases, the presentation order of items within each questionnaire was randomised for each participant. Questionnaires were administered digitally, with participants using their own smartphones to complete the online forms.

Preregistrations of statistical analysis

We conducted a preliminary analysis on the data from the first 10 participants and subsequently preregistered the analytical approach used on the remaining 48 participants on 2024-08-09 (https://osf.io/f9q6d/), after data collection but prior to any analysis on the preregistered sample. Therefore, we report the results of the preregistered analysis for the 48 participants separately from the complete results using the full sample. Processed data that includes all primary data and the custom codes for ECG data analysis are publicly available. Some materials and custom codes to run the experiments are not shared because of copyright restrictions, but available on reasonable request. The original version of the questionnaires used in this study are available from Kwon et al. [6] and Mehling et al. [35].

Classifying participants based on the behavioural data

All trials with RTs exceeding 3 SD from the average RT across individuals (i.e., RTs more than 787.71 ms) were excluded from further analyses, resulting in the removal of 275 out of 11,600 trials (approximately 2.37%). We hypothesised that smartphone-related distractors would affect participants differently depending on the task difficulty. Following the load theory of attention, we expected participants to show varying degrees of attentional bias towards smartphone stimuli, particularly under high perceptual load conditions[32,34]. To examine this, we calculated mean RTs for each condition (smartphone/control) and difficulty level (high/low) per participant. Then, the interaction index between condition and difficulty was calculated by subtracting the difference in RT between conditions under low load from the difference under high load. Negative values indicated greater distraction under low load, and positive values indicated greater distraction under high load.

We then performed K-means clustering (K = 2) using the interaction index as the input for each participant. This method aimed to differentiate participants with a consistent (i.e., under both low- and high-perceptual load) attentional bias toward smartphone stimuli from those who were only distracted during low-load tasks. Therefore, we expected the clustering to ideally separate participants into two groups: those with negative interaction index values (group 1) and those with positive or zero values (group 2). To validate the classification, we conducted repeated-measures ANOVAs with condition and difficulty as within-subject factors separately for each group. These ANOVAs were not intended to establish statistically significant group differences but to describe the pattern of results within each subgroup.

Association between the attentional bias and questionnaire data

We predicted that participants classified as having a consistent attentional bias (Group 2) would report lower interoceptive awareness. To test this, we conducted two-sample t-tests for each MAIA factor between the classified groups. Multiple comparisons were corrected using the Bonferroni method. We also compared SAS-SV scores between the groups using a two-sample t-test to determine whether the classification based on behavioural data corresponded to self-reported smartphone addiction. To further explore the direct relationship between attentional bias and questionnaire data, we conducted additional analyses treating attentional bias as a continuous variable. Specifically, we examined the correlation between the Interaction Index, derived from behavioural data, and individual scores on each factor of MAIA and SAS-SV. Spearman's ρ was used to assess these relationships because pairwise normality was not satisfied for at least two combinations of variables. These additional analyses strengthen the association between the attentional bias and questionnaire data, while deviating from the pre-registered strategy.

Instantaneous cardiac responses to stimulus presentation

We assessed cardiac responses to each stimulus across the classified groups, hypothesizing that groups would differ in their physiological reactivity to smartphone backgrounds. This analysis was exploratory and not pre-registered. Instantaneous heart rate changes were calculated and recorded at the end of each trial using the following procedures. First, a continuous time series of heart rate was derived from inter-beat intervals (IBI) using cubic spline interpolation, upsampled to a 10 Hz resolution[36]. Trials with erroneous heartbeat detection or skipped beats were excluded from further analysis, resulting in the removal of three trials. Each data point in the heart rate series was corrected by subtracting the most recent IBI value before stimulus onset, providing a measure of heart rate acceleration or deceleration at a 100 ms resolution on a trial-by-trial basis. The time window of interest extended from 500 ms before to 3000 ms after stimulus presentation. Unfortunately, we failed to record ECG data during experiments for 14 preregistered participants due to a wrong connection of the device that resulted in constant inputs; thus, data of the remaining 44 participants ($n = 24$ for group 1, $n = 20$ for group 2) was used for this analysis.

For statistical inference, we combined a hierarchical generalised linear model (individual-level analysis) with a summary statistic approach (group-level analysis). A generalised linear model was fit for each time bin for each participant, with random intercepts to account for individual variability. The design matrices encoded the main effects of condition, difficulty, their interaction, and RT. Group differences in these effects were tested using cluster-based permutation tests (500 permutations) based on two sample t-tests with a cluster extent correction for multiple comparisons ($p < 0.05$ cluster-extent correction). The height threshold for each t-test was adjusted using the Bonferroni method (i.e., 0.05/3 = 0.0167). These analysis codes and data are publicly available[37].

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Results

Observed attentional bias and participant subgroups

The 2-means clustering successfully divided the participants into two groups (group 1: $n = 32$; group 2: $n = 26$) (Fig. 1B). Group 1 showed a negative mean interaction index, indicating that participants in this group experienced greater distraction from smartphone stimuli under low-load conditions compared to high-load conditions as expected by the load theory of attention. In contrast, group 2 displayed a positive or near-zero mean interaction index, suggesting a consistent attentional bias towards smartphone stimuli as there was consistent distraction effect across both high and low-load tasks. Importantly, there was no significant difference in variance between the groups (Levene's test, $W = 0.694$, $p = .408$), which supports the effectiveness of a simple K-means clustering approach based on Euclidean distance. There was no significant group difference in age (group 1: 19.656 ± 1.842; group 2: 19.500 ± 1.393, $t_{56} = -0.357$, $p = .722$) and gender ratio (group 1: men = 14, women = 12; group 2: men = 14, women = 18, $\chi^2 = 0.586$, $p = 0.444$).

We tested the validity of the automated clustering by investigating the interaction between load and condition on RT, separately for each group. In group 1, repeated-measures ANOVAs revealed significant main effects of condition ($F_{1,\,31} = 14.855$, $\eta^2_p = .324$, 95% CI = [0.114, 0.999], $p < 0.001$), task load ($F_{1,\,31} = 100.940$, $\eta^2_p = 0.765$, 95% CI = [0.634, 0.999], $p < 0.001$), and their interaction ($F_{1,\,31} = 245.199$, $\eta^2_p = 0.888$, 95% CI = [0.821, 0.999], $p < .001$) (Fig. 1C). Post-hoc tests indicated slower RTs in the smartphone condition (373 ± 62 ms) compared to the control condition (342 ± 56 ms) in the low-load task ($t = 11.217$, corrected-$p < 0.001$), but the effect reversed in the high-load task (smartphone: 408 ± 73 ms; control: 420 ± 74 ms) ($t = -4.558$, corrected-$p < 0.001$). In contrast, in group 2, significant main effects of condition ($F_{1,\,25} = 19.141$, $\eta^2_p = 0.434$, 95% CI = [0.188, 0.999], $p < 0.001$) and difficulty ($F_{1,\,25} = 111.559$, $\eta^2_p = 0.817$, 95% CI = [0.695, 0.999], $p < .001$) were observed, but the interaction between them was not significant ($F_{1,\,25} = 1.428$, $\eta^2_p = 0.054$, 95% CI = [0.000, 0.999], $p = 0.243$). Confirmatory paired t tests revealed that Group 2 exhibited slower RTs in the smartphone condition compared to the control condition, even under high-load conditions (smartphone high: 418 ± 71 ms; control high: 406 ± 69 ms) ($t_{25} = -2.928$, uncorrected-$p = 0.007$, $d = -0.574$, 95 CI = [−0.985, −0.154]), as well as low-load condition (smartphone low: 365 ± 59 ms; control low: 350 ± 60 ms) ($t_{25} = -5.658$, $d = -1.110$, 95 CI = [−1.594, −0.611], uncorrected-$p < 0.001$). Importantly, the Bayesian repeated-measures ANOVA provided evidence against the alternative hypothesis for the condition × load interaction effect ($BF_{10} = 0.238$), suggesting a null interaction effect and a consistent attentional bias towards smartphone stimuli in Group 2.

The preregistered analysis, conducted with 48 participants, yielded similar findings. Participants were divided into two groups, which were then analysed (Group 1: $n = 23$; Group 2: $n = 25$). In group 1, significant main effects of condition ($F_{1,\,22} = 6.973$, $\eta^2_p = 0.241$, 95% CI = [0.031, 0.999], $p = 0.015$), task difficulty ($F_{1,\,22} = 62.885$, $\eta^2_p = 0.741$, 95% CI = [0.562, 0.999], $p < 0.001$), and their interaction ($F_{1,\,22} = 154.128$, $\eta^2_p = 0.875$, 95% CI = [0.781, 0.999], $p < 0.001$) were observed. Post hoc tests showed similar patterns to those in the full sample ($t = 9.962$, corrected-$p < 0.001$; $t = -5.898$, corrected-$p < 0.001$). In group 2, significant main effects of condition ($F_{1,\,24} = 16.752$, $\eta^2_p = 0.411$, 95% CI = [0.161, 0.999], $p < 0.001$) and difficulty ($F_{1,\,24} = 106.427$, $\eta^2_p = 0.816$, 95% CI = [0.690, 0.999], $p < 0.001$) were observed, but the interaction was not significant ($F_{1,\,24} = 2.755$, $\eta^2_p = 0.103$, 95% CI = [0.000, 0.999], $p = 0.110$). Confirmatory paired t test revealed that RTs were slower in the smartphone condition even under highly difficult tasks (smartphone high: 414 ± 71 ms; control high: 404 ± 69 ms) ($t_{24} = -2.644$, $d = -0.529$, 95 CI = [−0.943, −0.105], uncorrected-$p = 0.014$), as well as with low-load tasks (smartphone low: 362 ± 58 ms; control low: 347 ± 59 ms) ($t_{24} = -5.383$, $d = -1.077$, 95 CI = [−1.565, −0.574], uncorrected-$p < 0.001$). A Bayesian repeated-measures ANOVA provided evidence against the alternative hypothesis for the condition × load interaction effect ($BF_{10} = 0.315$).

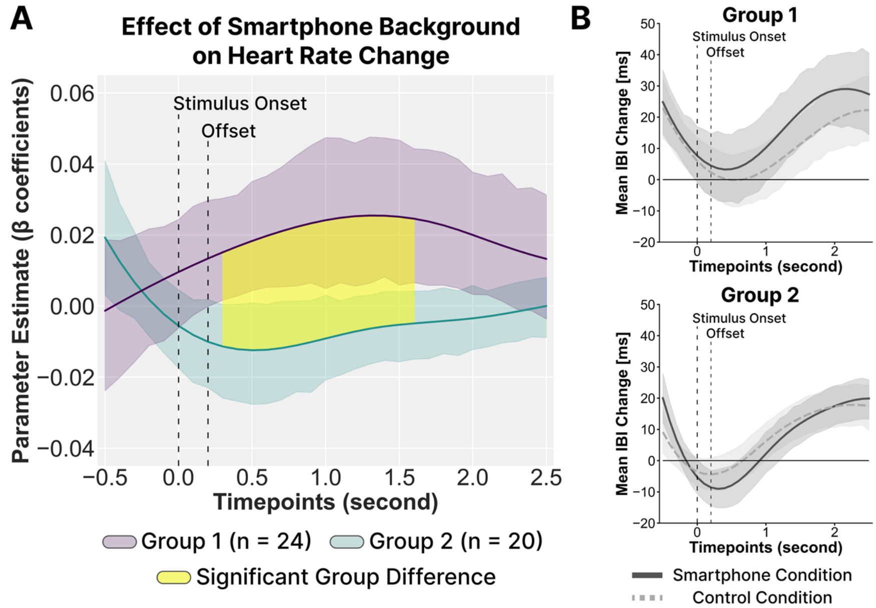

Fig. 2 | Instantaneous cardiac responses to smartphone stimuli across participant groups. **A** Parameter estimates (β coefficients) for heart rate changes following the presentation of smartphone stimuli across two groups of participants (Group 1: purple, Group 2: teal). Heart rate data were corrected for each participant by subtracting the most recent inter-beat interval (IBI) value before stimulus onset. The time course shows the group differences in heart rate responses, with significant differences (highlighted in yellow) observed between 300 ms and 1700 ms post-stimulus onset (cluster-based permutation test, $p = 0.002$, Bonferroni-corrected height threshold of $p < 0.017$). Group 1 exhibited a deceleration in heart rate after smartphone stimulus presentation, while Group 2 showed an acceleration. The dashed lines indicate the stimulus onset and offset. **B** Grand mean inter-beat-interval (IBI) changes (in milliseconds) over time for Group 1 (top) and Group 2 (bottom), comparing the smartphone condition (solid lines) and control condition (dashed lines). Group 1 displayed a pronounced deceleration of heart rate in response to the smartphone background. In contrast, Group 2 showed an acceleration in heart rate in response to smartphone stimuli. Error bars represent standard errors of the mean.

Relationship between decreased interoceptive awareness and attentional bias

Importantly, group 2 exhibited significantly lower scores on the noticing and trusting factors of the MAIA compared to group 1, indicating reduced subjective awareness of bodily sensations and a lower tendency to trust these sensations as safe ($t_{56} = -3.951$, $d = -1.043$, 95% CI = [−1.591, −0.487], corrected-$p = 0.003$; $t_{56} = -3.740$, $d = -0.987$, 95% CI = [−1.532, −0.435], corrected-$p = 0.003$, respectively) (see Table 1 for full results). Additionally, group 2 scored significantly higher on the SAS-SV ($t_{56} = 2.455$, $d = 0.648$, 95% CI = [0.114, 1.177], $p = 0.017$), reflecting greater self-reported smartphone addiction. Further analyses treating attentional bias as a continuous variable supported these findings. Spearman's ρ revealed significant negative correlations between the Interaction Index and the noticing (Spearman's $\rho = -0.411$, 95% CI = [−0.598, −0.169], Bonferroni corrected-$p = 0.008$) and trusting ($\rho = -0.376$, 95% CI = [−0.521, −0.132], corrected-$p = 0.032$) subscales of the MAIA, suggesting that greater attentional bias was associated with diminished interoceptive awareness in these dimensions. Additionally, a significant positive correlation was found between the Interaction Index and SAS-SV scores ($\rho = 0.336$, 95% CI = [0.091, 0.563], $p = 0.010$), suggesting that higher attentional bias was linked to greater self-reported problematic smartphone use.

Consistent with the full sample, the preregistered analysis revealed significant group differences in MAIA factors, with group 2 scoring lower on noticing and trusting ($t_{46} = -3.485$, $d = -1.007$, 95% CI = [−1.604, −0.400], corrected-$p = 0.008$; $t_{46} = -3.057$, $d = -0.883$, 95% CI = [−1.473, −0.285], corrected-$p = 0.032$, respectively). Group 2 scored significantly higher on the SAS-SV than group 1 ($t_{46} = 2.294$, $d = 0.663$, 95% CI = [0.077, 1.242], $p = 0.026$). Supporting these findings, the same significant correlation trends appeared in the preregistered sample when using the interaction index as continuous value, except MAIA trusting: MAIA noticing ($\rho = -0.398$, 95% CI = [−0.614, −0.157], corrected-$p = 0.040$), MAIA trusting ($\rho = -0.345$, 95% CI = [−0.573, −0.058], corrected-$p = 0.128$), and SAS-SV ($\rho = 0.350$, 95% CI = [0.053, 0.606], $p = 0.015$).

Instantaneous heart rate changes against smartphone stimuli

Significant group differences in cardiac response were observed following the presentation of letter strings, which were superimposed on smartphone images. In the low-attention bias group (group 1), heart rate decelerated in response to the smartphone background compared with scrambled one, whereas in group 2, who exhibited greater attentional bias to smartphone stimuli, it accelerated. This group difference emerged as a significant effect of condition between 300 ms and 1700 ms after stimulus onset (cluster-extent correction, permutation $p = 0.002$; height threshold: $p < .017$) (Fig. 2A, B). No significant group differences were found for the effects of task difficulty or the interaction between condition and difficulty (uncorrected $ps \geq 0.082$ at each time point).

In the preregistered analysis, no statistically significant clusters were identified for the effect of condition when applying the same statistical methods (uncorrected $ps \geq 0.019$ at each time point). However, when the Bonferroni correction for the height threshold was removed (uncorrected $p < 0.05$), significant group differences emerged from 200 ms to 2200 ms post-stimulus onset (cluster-extent correction, permutation $p = 0.002$), indicating a possible but weaker effect compared to the full sample analysis.

Discussion

The present study investigated attentional biases towards smartphone-related stimuli and their relationship with interoceptive awareness and physiological cue reactivity in healthy young adults. By employing a letter detection task with varying perceptual loads and measuring cardiac responses, we sought to elucidate the cognitive and physiological mechanisms underlying smartphone-related attentional capture. Unlike dot-probe tasks, which measure attentional orienting towards or away from specific cues, the letter detection paradigm focuses primarily on selective attention, providing a framework to investigate how attentional processes interact with task demands. As expected, our findings revealed two distinct patterns of attentional bias among participants, which contributes to understanding how smartphone stimuli interact with cognitive load and individual differences in interoceptive processing.

Consistent with the load theory of attention, one group of the current participants (group 1) exhibited greater distraction from smartphone stimuli under low-load conditions, suggesting that task-irrelevant smartphone images more easily capture attention than scrambled one among healthy populations, when cognitive resources are readily available[34]. Under high-load conditions, where cognitive resources are taxed, these participants were

Table 1 | Comparison of multidimensional assessment of interoceptive awareness (MAIA) subscale scores and smartphone addiction scale short version (SAS-SV) scores between groups with and without consistent attentional bias toward smartphone stimuli

	Group 1 Mean	Group 2 Mean	Group Difference t_{56}	Uncorrected-*p*	Effect Size d	Correlation *rho*	Uncorrected-*p*
MAIA							
Noticing	3.516 ± 0.971	2.327 ± 1.319	3.951	<0.001	1.043 ± 0.301	−0.411	0.001
Not Distracting	2.859 ± 0.971	2.327 ± 0.999	2.024	0.048	0.534 ± 0.274	−0.208	0.117
Not Worrying	2.594 ± 0.871	2.205 ± 0.953	1.621	0.111	0.428 ± 0.271	−0.218	0.108
Attention Control	2.330 ± 0.618	2.049 ± 0.681	1.644	0.106	0.434 ± 0.271	−0.315	0.016
Emotional Awareness	2.438 ± 0.962	1.769 ± 0.868	2.747	0.008	0.725 ± 0.283	−0.273	0.038
Self-control	2.453 ± 0.750	2.000 ± 1.155	1.802	0.077	0.476 ± 0.272	−0.237	0.074
Body Listening	2.198 ± 0.957	1.551 ± 0.952	2.565	0.013	0.677 ± 0.280	−0.307	0.019
Trusting	2.687 ± 1.002	1.782 ± 0.800	3.740	<0.001	0.987 ± 0.297	−0.376	0.004
SAS-SV total	28.063 ± 7.103	32.269 ± 5.640	−2.455	0.017	-0.648 ± 0.279	0.336	0.010

Two-sample *t* tests were conducted for each variable, and Spearman's rho was calculated to assess correlations between attentional bias (interaction index) and questionnaire scores. Group 2, which exhibited a consistent attentional bias, reported significantly lower scores on the noticing and trusting subscales of the MAIA, reflecting reduced interoceptive awareness, and significantly higher scores on the SAS-SV, indicating greater self-reported smartphone addiction. Multiple comparisons for MAIA subscales were corrected using the Bonferroni method. Mean value with standard deviations, *t* values, uncorrected *p* values, effect sizes (Cohen's d) with standard errors, and Spearman's rho values with their associated uncorrected *p* values are presented.

less susceptible to distraction, indicating effective attentional filtering. In contrast, a second group (group 2) demonstrated a consistent attentional bias towards smartphone stimuli regardless of task difficulty. Their slower RTs in the smartphone condition persisted even under high perceptual load, suggesting that for these individuals, smartphone stimuli hold a privileged status in attentional processing. This pervasive attentional capture implies automaticity in processing smartphone cues, potentially reflecting habitual use or heightened salience attributed to these stimuli[10]. These findings are consistent with previous research on attentional biases in behavioural addictions and suggest that smartphone-related stimuli may capture attention similarly to addiction-related cues[16,17,38]. The heterogeneity in attentional capture underscores the importance of considering individual differences in susceptibility to distraction by technology-related stimuli. This variability may help explain inconsistent findings in prior studies examining attentional bias to smartphone cues[21,22]. It suggests that attentional biases towards smartphone stimuli are not uniform across individuals but may depend on personal factors such as habitual use patterns or underlying cognitive processes.

A key finding of this study is the association between consistent attentional bias towards smartphone stimuli and reduced interoceptive awareness. Participants in group 2, who exhibited attentional bias under both low- and high-perceptual load, scored significantly lower on the noticing and trusting subscales of the MAIA. This indicates a subjectively reduced tendency to perceive and trust internal bodily signals. Impaired interoceptive awareness has been implicated in addictive behaviours, suggesting that individuals less attuned to their internal states may rely more heavily on external cues, such as smartphone notifications, to regulate emotions or relieve discomfort[25,26]. The higher scores on the SAS-SV in group 2 further support this notion, indicating a greater tendency towards problematic smartphone use. These results suggest a potential mechanism wherein reduced interoceptive awareness is tied with heightened attentional capture by smartphone stimuli, reinforcing excessive use patterns. Our findings align with recent studies reporting reduced interoceptive awareness in individuals with behavioural addictions[24,27], extending this relationship to potential excessive technology dependence.

The physiological data complement the behavioural findings, revealing distinct patterns of cardiac responses to smartphone stimuli between the groups. Group 1 exhibited heart rate deceleration following the presentation of smartphone images, typically associated with attentional orienting and information intake[39]. In contrast, group 2 showed heart rate acceleration, suggesting heightened arousal or emotional reactivity[36,40]. These responses align with cue-reactivity models of addiction, where exposure to addiction-related cues triggers physiological arousal, which has been associated with craving and compulsive behaviours[10,13]. The heart rate acceleration in Group 2 suggests that smartphone cues evoke an automatic physiological response in individuals more susceptible to a prolonged addictive cycle. Importantly, cardiac responses to task difficulty, as well as the interaction between condition and difficulty, did not significantly differ between the groups, indicating that the altered cardiac responses in Group 2 are specific to the background images. This reinforces the notion that smartphone-related stimuli uniquely trigger heightened physiological arousal, independent of cognitive load.

The identification of attentional capture patterns highlights the heterogeneous nature of smartphone use and its potential implications for understanding problematic usage, suggesting avenues for future research. We found that while some individuals are distracted by smartphone stimuli only under low cognitive load, others exhibit persistent attentional bias regardless of task demands. These findings suggest that habitual smartphone use may broadly alter attentional processes even in a healthy population, a phenomenon that could be increasingly inevitable in today's digital landscape. Therefore, further studies are needed to investigate how patterns of attentional bias and cue reactivity develop over time and at which stages these responses emerge. For example, examining activity in the insular cortex, a region implicated in both interoceptive awareness and addiction[28,41], could shed light on the neural mechanisms underlying these behavioural and physiological patterns. Additionally, testing whether enhancing interoceptive awareness can reduce these cue-response cycles is crucial for developing better treatments. Since mindfulness-based interventions have shown effectiveness in reducing excessive smartphone use[30,31], future clinical approaches may benefit from more targeted and streamlined strategies.

Limitations

The current study provides a multidimensional examination of attentional bias toward smartphones from behavioural, psychological, and physiological perspectives. Some may suggest using more detailed assessments of smartphone addiction, including phone usage statistics and formal psychiatric diagnoses, to strengthen the connection to clinical addiction[42,43]. However, we believe that studying healthy young adults offers a valuable perspective, as it allows us to identify early-stage cognitive and physiological markers of problematic smartphone use before full-blown addiction develops. This approach also provides critical insights into how attentional bias and interoceptive awareness are affected in a general population, which can later inform research on clinical populations. By segmenting participants based on behaviour, we effectively characterised attentional bias towards marginal smartphone-related information and its association with reduced interoceptive awareness and heightened physiological reactivity. This approach is particularly relevant given the pervasive role of smartphones in modern life, where many individuals use smartphones extensively for purposes such as work or communication. In this context, we recognise that our findings may reflect attentional bias related to the habitual use of smartphones rather than their specific visual features. The smartphone stimuli used in this study depicted common usage scenarios such as home screens, alarms, and chat interfaces, which may reflect their relevance to habitual smartphone use and therefore contribute to their salience. Future research incorporating alternative stimuli, such as other frequently used devices, would help clarify whether the observed effects are specific to smartphones or represent a broader attentional bias toward commonly used technology. Additionally, the generalisability of our findings may be limited by our sample of Japanese young adults. Given potential cultural differences in the prevalence of excessive smartphone use between Western and Eastern societies[44,45], replicating this study with diverse populations would be valuable. Furthermore, it should be noted that the randomisation of questionnaire items, which was intended to minimise order effects and response bias, may have influenced the measures compared to their original forms.

Conclusions

This study indicates that attentional bias towards smartphone stimuli is associated with reduced interoceptive awareness and heightened physiological reactivity in healthy young adults. The findings suggest that for some individuals, smartphone cues possess heightened salience capable of capturing attention even under high cognitive load, potentially enhancing excessive use patterns. By elucidating the interplay between attentional processes, interoceptive awareness, and physiological responses, this research advances our understanding of the cognitive mechanisms underlying problematic smartphone engagement. As digital technology continues to permeate daily life, these insights are vital for informing interventions and policies aimed at promoting healthier technology use.

Data availability

All data supporting the current study, trial-by-trial responses and heart rate changes associated with each trial, are publicly available in the Open Science Framework repository at https://osf.io/f9q6d/.

Code availability

Our custom codes for heart rate analysis, including the hierarchical generalised linear model and permutation tests, are publicly available in the Open Science Framework repository at https://osf.io/f9q6d/. Custom codes to run the experiment are not shared due to copyright restrictions.

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Author contributions

Y.H., (Corresponding Author): Conceptualisation, Methodology, Software, Formal Analysis, Data Curation, Writing—Original Draft, Writing—Review & Editing, and Visualisation. K.M.: Conceptualisation, Funding Acquisition, and Writing—Review & Editing. K.O.: Conceptualisation, Resources, Supervision, and Writing—Review & Editing. K.S. (Corresponding Author): Conceptualisation, Resources, Funding Acquisition, Project Administration, and Writing—Review & Editing.

Competing interests

The authors declare no competing interests.

Additional information

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