



The sacrifice of alerting in active short video users: Evidence from executive control and default mode network functional connectivity

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ABSTRACT

Human attention is a limited resource increasingly taxed by continuous, socially embedded media streams, but how habitual short-video use shapes core attentional operations and their neural substrates remains unclear. Here we distinguish active from passive short video usage and examine whether they differentially relate to the alerting, orienting, and executive components of attention and to large-scale resting-state network connectivity. Our results demonstrate that frequent active short video usage predicts reduced alerting efficiency and the functional connectivity between right ventral prefrontal cortex (PFCv) and right posterior cingulate cortex (PCC) mediates this association, attenuating the direct effect and implicating interactions between default mode network (DMN) and control network. While orienting exhibits a modest interaction among different usages in which higher passive usage confers greater orienting only among low-active users, and executive control shows no reliable association. These findings extend resource-control accounts of attention to the short-video context by identifying a specific, right-lateralized coupling between brain networks that links active usage to diminished alerting. Mechanistically, we identify a right-lateralized default-control coupling that mediates the link between active short video usage and reduced alerting, isolating a modifiable resting-state pathway. These results provide actionable metrics for intervention and platform design to mitigate attentional costs in high-exposure users, informing evidence-based guidance for education and policy.

1. Introduction

Digital media has progressively reorganized how attentional resources are allocated, consistent with resource-control accounts positing performance costs under concurrent demands (Huang et al., 2023). Empirical reports link heavy social-media engagement to reduced sustained attention and diminished visual-search efficiency (Guo et al., 2024; Fu et al., 2018), yet these findings derive largely from cross-sectional behavioral designs with self-reported exposure and heterogeneous task paradigms, complicating causal interpretation and comparability across studies. As one of the most pervasive formats, short-video use has further been associated with impaired attentional control (Yan et al., 2024; Walla and Zheng, 2024), but prior work often aggregates distinct usage modes and thereby obscures potential mode-specific effects on the attention network; critically, the neural

mechanisms that may mediate these behavioral associations remain insufficiently characterized.

Short video usage is commonly parsed into active usage and passive usage. Active usage entails receiving and processing social information during viewing followed by interpersonal exchange in line with social norms whereas passive usage denotes observing others' content without direct interaction, such as watching videos and comments (Verduyn et al., 2022; Zhai et al., 2024). Active usage involves socially contingent behaviors such as giving and receiving Likes and commenting, and consistently engages valuation and social-cognition systems, including the striatum, ventral tegmental area, and nucleus accumbens, together with medial prefrontal and posterior midline hubs and the bilateral temporoparietal junction (TPJ); these patterns indicate reinforcement learning, social reward processing, and self-referential appraisal during this interactive short-video behavior (Sherman et al., 2018a, 2018b).

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Complementarily, regions frequently discussed for active usage include medial prefrontal cortex (PFCm) and posterior cingulate cortex (PCC) within the default mode network (DMN), the ventral prefrontal cortex (PFCv) and orbitofrontal cortex (OFC) implicated in social-emotional evaluation, and the temporal pole (TP) linked to affective meaning and person knowledge (Herlin et al., 2021; Nelson and Guyer, 2011). By contrast, passive usage centers on viewing personalized streams and has been associated with activation of the DMN and ventral tegmental area and with modulation of coupling among large-scale networks along routes described as Dorsal Attention Network (DAN) to Frontoparietal Network-Core Network (FPN) to Core and DAN to Ventral Attention Network (VAN) to dorsal PFCm, consistent with externally oriented attention that co-occurs with self-referential processing (Su et al., 2021a, 2021b). Taken together, the literature points to partially distinct neurocognitive routes for active usage and passive usage, yet direct evidence for a mechanistic dissociation at the level of intrinsic connectivity in habitual users remains limited, motivating the present focus on resting-state pathways that could differentiate the two modes.

As a fundamental cognitive function, attention can be shaped by media usage, including short videos, games, and social media, and is commonly parsed into three sub-networks: alerting, orienting, and executive control (Petersen and Posner, 2012). The alerting network supports achieving and sustaining readiness and relies on a right-hemisphere system encompassing the thalamus, frontal cortex, and parietal cortex (Petersen and Posner, 2012; Hao et al., 2015). Experimental evidence indicates that a single session of mobile action video game play improves alerting efficiency (Wang et al., 2023) and that pairing action video game training with posterior parietal cortex neuromodulation further enhances alerting in adults with developmental dyslexia (Bertoni et al., 2024). The orienting network subserves selective attention to external information and involves the parietal cortex, superior colliculus, and frontal eye fields (Petersen and Posner, 2012; Xuan et al., 2016). Consistent with this role, action video game players show advantages in orienting across visual and auditory modalities (Mancarella et al., 2022; Wu et al., 2021), although media multitasking has been linked to reduced orienting efficiency (Wu and Cheng, 2019). The executive control network resolves response conflict and engages the medial frontal cortex and the midline anterior cingulate cortex (Petersen and Posner, 2012). Training studies report improved attentional control following action video game play in children with developmental dyslexia (Bertoni et al., 2021), whereas EEG findings associate higher prefrontal theta power under high control demands with short video addiction, suggesting possible executive control vulnerability (Yan et al., 2024). Overall, prior work has emphasized games as a model for plasticity in attention networks; in comparison, the neural mechanisms linking different ways of short video usage to specific sub-networks remain insufficiently characterized.

Resting-state fMRI captures spontaneous brain activity in the absence of explicit tasks (Lv et al., 2018). Intrinsic patterns derived from these data are sensitive to experience-dependent alterations linked to prolonged media behaviors (Afra et al., 2023; Wadsley and Ihssen, 2023; Zeng et al., 2023). Within this framework, functional connectivity indexes the temporal synchrony of BOLD signals between regions, providing an assay of putative information exchange (Suarez et al., 2020). Higher synchrony suggests coordinated engagement in shared computations, and multiregional synchrony composes large-scale brain networks (Faskowitz et al., 2022). Accordingly, we used resting-state fMRI to test whether long-term short video usage maps onto intrinsic coupling patterns, with specific attention to how active usage and passive usage relate to networks supporting attention, control, and self-referential processing.

The present study therefore examined the relationship between short video usage and attention networks in two experiments. Experiment 1 employed behavioral assays to estimate efficiencies of the alerting, orienting, and executive control sub-networks as a function of active usage and passive usage. Experiment 2 used resting-state fMRI to

identify intrinsic connectivity patterns associated with usage modes and to evaluate whether connectivity provides mechanistic links to behavioral differences. Guided by resource-control account, we hypothesized that active usage would exert a stronger influence on specific attention sub-networks than passive usage, and that these associations would be reflected in dissociable intrinsic connectivity signatures.

2. Experiment 1: Behavioral study on short video usage and attention network

Recent work links frequent Short video usage to attentional impairments (Yan et al., 2024; Walla and Zheng, 2024). Whether distinct usage patterns exert consistent or dissociable effects across the attention sub-networks, however, remains unresolved. To address this, we administered a questionnaire to quantify active usage and passive usage and employed the Attention Network Test (ANT) to estimate alerting, orienting, and executive control. Guided by this distinction, we hypothesized that active usage would exert a stronger impact on a subset of attention sub-networks.

2.1. Methods and materials

2.1.1. Participants

A total of 319 participants completed the Short Video Usage Questionnaire, the Short Video Addiction Scale (SVA), and the ANT. Of these, 204 participants completed the tasks online via the NAODAO research platform (61 males; Mage = 23.52, SD = 5.82; Chen et al., 2023), and 115 participants were tested offline at a university in China (48 males; Mage = 20.50, SD = 1.94). All participants provided informed consent prior to data collection and received compensation for their time. The study protocol was approved by Tianjin Normal University ethics committee (2025030311).

2.1.2. Short Video Usage Questionnaire

The Short Video Usage Questionnaire developed by Li (2016) was adapted to fit the context of short video usage. Participants responded to the items on a 5-point scale ranging from “1 = never” to “5 = several times a day” to assess the frequency of each short video usage behavior. Since passive usage emphasizes using short videos without directly participating in social interactions, participants were reminded to exclude active usage when estimating the frequency of passive usage. Before the formal experiment, to ensure the validity of the measurement tools, we recruited 1,053 participants to complete the questionnaire through online platforms. An exploratory factor analysis was conducted, with a KMO value of 0.848. The Bartlett’s test of sphericity was significant ($\chi^2 = 2578.053$, $df = 91$, $p < 0.001$), indicating that the scale is suitable for exploratory factor analysis. Principal axis factoring and Promax rotation were used to determine the number of factors based on the eigenvalue criterion of greater than or equal to 1, and the scree plot. Three types of items were excluded: those with a communality less than 0.3, those with absolute factor loadings less than 0.3, and those with absolute differences in loadings less than 0.15 across multiple factors. Following the exclusion of each item, exploratory factor analysis was repeated until no items satisfied any of the criteria. The result was two dimensions: 7 items remained for active use, such as “liking,” and 5 items remained for passive use, such as “browsing recommended videos.” The cumulative contribution rate was 46.9 %. Confirmatory factor analysis results showed $\chi^2/df = 3.449$, RMSEA = 0.068, GFI = 0.945, TLI = 0.919, and CFI = 0.936, all exceeding 0.90, indicating the model is reasonably fit. The sum of the active use items was taken as the active usage score, and the sum of the passive usage items as the passive usage score. The Cronbach’s α for active usage was 0.747, and for passive usage, it was 0.804.

2.1.3. Short Video Addiction Scale

Because short video addiction has been associated with differences in

cognition and attention (Liao, 2024; Yan et al., 2024), SVA scores were included as a covariate. The SVA used here was adapted from Chao et al. (2023) and comprises 10 items rated on a 6-point Likert-type scale (1 = strongly disagree to 6 = strongly agree), with higher totals indicating greater intensity of use and stronger dependence tendency. To classify probable addiction, we applied sex-specific cutoff scores established in prior validation work: total score ≥ 33 for females and ≥ 31 for males; scores below these thresholds were classified as non-addicted. By these criteria, 53.43 % of participants met the cutoff for probable addiction. Internal consistency was excellent (Cronbach's $\alpha = .913$).

2.1.4. Attention Network Test (ANT)

The ANT estimates the efficiency of three attention sub-networks, including alerting, orienting, and executive control, by contrasting response times across cueing and flanker conditions (Fan et al., 2002). The alerting network supports achieving and maintaining readiness for incoming stimuli; the orienting network supports the selection of task-relevant sensory information; and the executive control network resolves response conflict. Network efficiencies were computed from condition-wise response time differences following established procedures (De Souza Almeida et al., 2021).

A schematic of each trial is included in Fig. 1. A fixation cross was continuously displayed at the center of the screen. Each trial began with 400 ms of fixation, followed by a 100 ms asterisk cue. After a further 400 ms fixation, an array of five arrows appeared either above or below fixation. The central arrow was the target (left- or right-pointing); the two flanking arrows on each side served as distractors and were either congruent or incongruent with the target direction. Participants indicated the target's direction with the left or right arrow key as quickly and accurately as possible. The response window was 1,700 ms from array onset. Each trial ended with a 400 ms fixation, yielding a fixed trial duration of 4,000 ms.

The task used a 3 (cue type) \times 2 (flanker type) factorial design. Cue types were: no cue (no asterisk before the array), center cue (asterisk at fixation), and spatial cue (asterisk above or below fixation indicating the upcoming target location; 100 % valid). Flanker types were congruent and incongruent. Each of the six conditions contained 16 trials (96 trials per block). Two blocks were administered for a total of 192 trials. Twelve practice trials preceded the formal task. The task lasted approximately 15 min.

Reaction time (RT) and accuracy were recorded for each condition. Efficiency scores were computed as follows:

$$\text{Alerting} = \text{RT}_{(\text{no cue})} - \text{RT}_{(\text{center cue})}$$

$$\text{Orienting} = \text{RT}_{(\text{center cue})} - \text{RT}_{(\text{spatial cue})}$$

$$\text{Executive control} = \text{RT}_{(\text{incongruent})} - \text{RT}_{(\text{congruent})}$$

Larger alerting and orienting values indicate greater benefit from cues, whereas larger executive control values indicate a larger conflict cost and therefore lower control efficiency.

On each trial, participants maintained fixation on a central cross and indicated the direction of the central target arrow (left or right) via keypress. Trials began with 400 ms fixation, a 100 ms cue, and a further

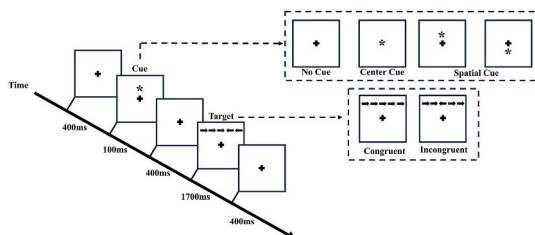


Fig. 1. Attention Network Test (ANT) paradigm.

400 ms fixation, followed by a five-arrow array presented above or below fixation; the four flanking arrows were either congruent (same direction as the target) or incongruent (opposite direction). Cue conditions were no cue (absent), center cue (asterisk at fixation), and spatial cue (asterisk above or below fixation; 100 % valid for target location). The response window was 1,700 ms from array onset, after which a 400 ms fixation completed the 4,000 ms trial.

2.1.5. Statistical analyses

To ensure data quality, we excluded participants with overall accuracy < 60 %. At the trial level, we removed responses < 100 ms and responses with RTs beyond ± 3 SD of each participant's mean. All statistical analyses were performed in IBM SPSS Statistics 27.0.1.0.

Our analyses were organized to move from descriptive group comparisons to model-based prediction: (i) establish usage-based groups to compare core performance profiles; (ii) test whether RT varies as a function of usage mode and task manipulations (cue, flanker); (iii) examine group differences in ANT efficiency indices; (iv) assess error-related outcomes with distribution-appropriate tests; and (v) evaluate whether active usage and passive usage uniquely predict network efficiencies beyond covariates.

To define usage-based cohorts for between-group contrasts, participants were dichotomized on active usage and passive usage by their respective medians, yielding four cohorts: ActH-PaH (high active and high passive users, $n = 83$), ActH-PaL (high active and low passive users, $n = 83$), ActL-PaH (low active and high passive users, $n = 79$), and ActL-PaL (low active and low passive users, $n = 74$). We verified the manipulation by testing that groups differed on their intended usage scores (see Section S1).

To test how usage modes interact with cueing and conflict demands, we conducted a 2 (Active group: high, low) \times 2 (Passive group: high, low) \times 3 (Cue: none, center, spatial) \times 2 (Flanker: congruent, incongruent) mixed-design ANOVA with RT as the dependent variable. Active and Passive were between-subject factors; Cue and Flanker were within-subject factors. To account for potential confounds, we included SVA, gender, age, and testing location as covariates (ANCOVA). Assumptions were examined prior to inference: Levene's tests supported homogeneity of variance; residual diagnostics indicated minor deviations from normality, for which the planned parametric models are considered robust given the sample size (Blanca et al., 2017); Greenhouse-Geisser corrections were applied where sphericity was violated.

To probe usage-related differences in alerting, orienting, and executive control, we conducted separate 2 (Active group) \times 2 (Passive group) between-subject ANCOVA on each ANT efficiency score (alerting, orienting, executive control), again controlling for SVA, gender, age, and testing location. This analysis targets whether usage modes are associated with differential benefits of cueing or costs of conflict at the summary index level.

Furthermore, according to Johnson et al. (2008), to compare accuracy outcomes where distributions are non-normal/zero-inflated and because incorrect responses and omissions tend to be skewed and sparse, we used non-parametric tests, with incorrect responses and omissions analyzed separately (see Section S2).

Finally, to test whether usage continuously predicts ANT efficiencies after accounting for covariates, we built hierarchical linear regression models. Step 1 included gender, age, SVA, testing location, and the other two ANT efficiencies (to isolate variance specific to the target network). Step 2 added active usage, passive usage, or both, yielding nine total models (three outcomes \times three predictor sets). Standard diagnostics (linearity, homoscedasticity, influential points, multicollinearity) were checked prior to interpretation.

2.2. Results

The results of the mixed-design ANCOVA, with Active Group, Passive Group, Cue, and Flanker as factors and RT as the dependent variable, are

shown in Fig. 2. The main effect of Cue was significant, $F(2, 310) = 28.44, p < .001, \eta^2 = .16$. RTs in the spatial cue condition ($M = 552.28$ ms, $SE = 3.98$) was significantly shorter than in the center cue ($M = 593.76$ ms, $SE = 3.85$) and no cue ($M = 603.05$ ms, $SE = 3.90$) conditions. The main effect of Flanker was significant, $F(1, 311) = 70.61, p < .001, \eta^2 = .19$. RTs in the congruent condition ($M = 541.85$ ms, $SE = 3.69$) was significantly shorter than in the incongruent condition ($M = 624.21$ ms, $SE = 4.19$). These findings align with previous research, supporting the validity of the experimental paradigm.

The Cue \times Active-Group interaction was significant, $F(2, 310) = 3.28, p = .039, \eta^2 = .02$. For the low-active group, $F(2, 310) = 286.15, p < .001, \eta^2 = .65$: RTs in the spatial-cue condition ($M = 552.27$ ms, $SE = 5.89$) were significantly shorter than in the center cue ($M = 591.91$ ms, $SE = 5.70$) and no cue ($M = 603.75$ ms, $SE = 5.78$) conditions. For the high-active group, $F(2, 310) = 309.58, p < .001, \eta^2 = .67$: RTs in the spatial cue condition ($M = 552.29$ ms, $SE = 5.64$) were significantly shorter than in the center cue ($M = 595.62$ ms, $SE = 5.45$) and no cue ($M = 602.36$ ms, $SE = 5.53$) conditions.

The Cue \times Active Group \times Passive Group interaction was significant, $F(2, 310) = 3.54, p = .03, \eta^2 = .02$. RTs in the spatial cue condition were significantly shorter than in the center cue condition, which in turn were shorter than in the no cue condition across all Active \times Passive subgroups: ActH-PaH, $F(2, 310) = 154.26, p < .001, \eta^2 = .50$; ActH-PaL, $F(2, 310) = 150.21, p < .001, \eta^2 = .49$; ActL-PaH, $F(2, 310) = 186.55, p < .001, \eta^2 = .55$; and ActL-PaL, $F(2, 310) = 107.43, p < .001, \eta^2 = .41$. By contrast, the four subgroups did not differ at any cue level: no-cue, $F(3, 311) = 0.23, p = .873$; center-cue, $F(3, 311) = 0.50, p = .680$; and spatial-cue, $F(3, 311) = 1.00, p = .392$. These results indicate that, although all subgroups exploited cue information in the canonical order (spatial < center < no cue), the magnitude of the cueing benefit

varied by usage profile, with maximal in ActL-PaH ($\eta^2 = .55$) and minimal in ActL-PaL ($\eta^2 = .41$), implicating differences in cue sensitivity rather than baseline speed, given the absence of between-group RT differences within any cue level.

A mixed-design ANCOVA was conducted with Active Group and Passive Group as factors, and ANT efficiency as the dependent variable, are shown in Fig. 3. For alerting efficiency, the main effect of Active Group was significant, $F(1, 311) = 6.97, p = .009, \eta^2 = .02$. Participants in the low-active subgroup showed greater alerting efficiency ($M = 12.30$ ms, $SE = 1.47$) than those in the high-active subgroup ($M = 6.82$ ms, $SE = 1.40$).

For orienting efficiency, the interaction between Active Group and Passive Group was significant, $F(1, 311) = 5.65, p = .018, \eta^2 = .02$. Simple effects tests revealed that orienting efficiency was higher in the ActL-PaH ($M = 44.36$ ms, $SE = 2.78$) than in the ActL-PaL ($M = 33.49$ ms, $SE = 2.98$), $F(1, 311) = 7.19, p = .008, \eta^2 = .02$, whereas no difference emerged between ActH-PaH ($M = 41.29$ ms, $SE = 2.77$) and ActH-PaL ($M = 43.63$ ms, $SE = 2.74$), $F(1, 311) = 0.37, p = .546$. This pattern indicates that higher passive usage is associated with better orienting efficiency only when active usage is low, whereas at high active usage the orienting benefit of passive usage disappears.

For executive control efficiency, the main effect of Active Group, $F(1, 311) = 0.09, p = .770$, the main effect of Passive Group, $F(1, 311) = 0.03, p = .867$, nor the Active \times Passive interaction, $F(1, 311) = 0.33, p = .566$, did not reach significance.

Before conducting the hierarchical regression analyses, all statistical assumptions were checked. The Durbin-Watson statistic was 1.87, which falls within the acceptable range of 1.5 to 2.5, indicating independence of residuals. Partial regression plots confirmed approximate linear relationships, and the scatterplot of standardized residuals

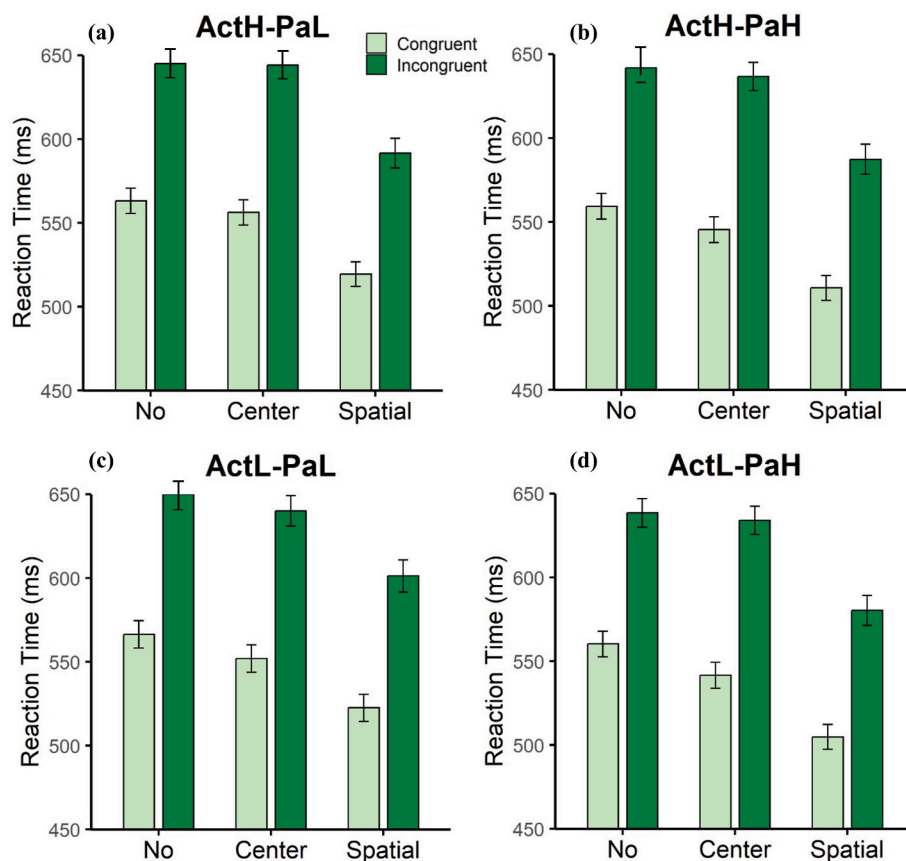


Fig. 2. RTs by cue and flanker across Active \times Passive groups.

(a) ActH-PaH ($n = 83$), (b) ActH-PaL ($n = 83$), (c) ActL-PaH ($n = 79$), (d) ActL-PaL ($n = 74$). Each panel plots mean RT (ms) for congruent and incongruent flankers under the three cue conditions (no, center, spatial). Error bars denote \pm SE.

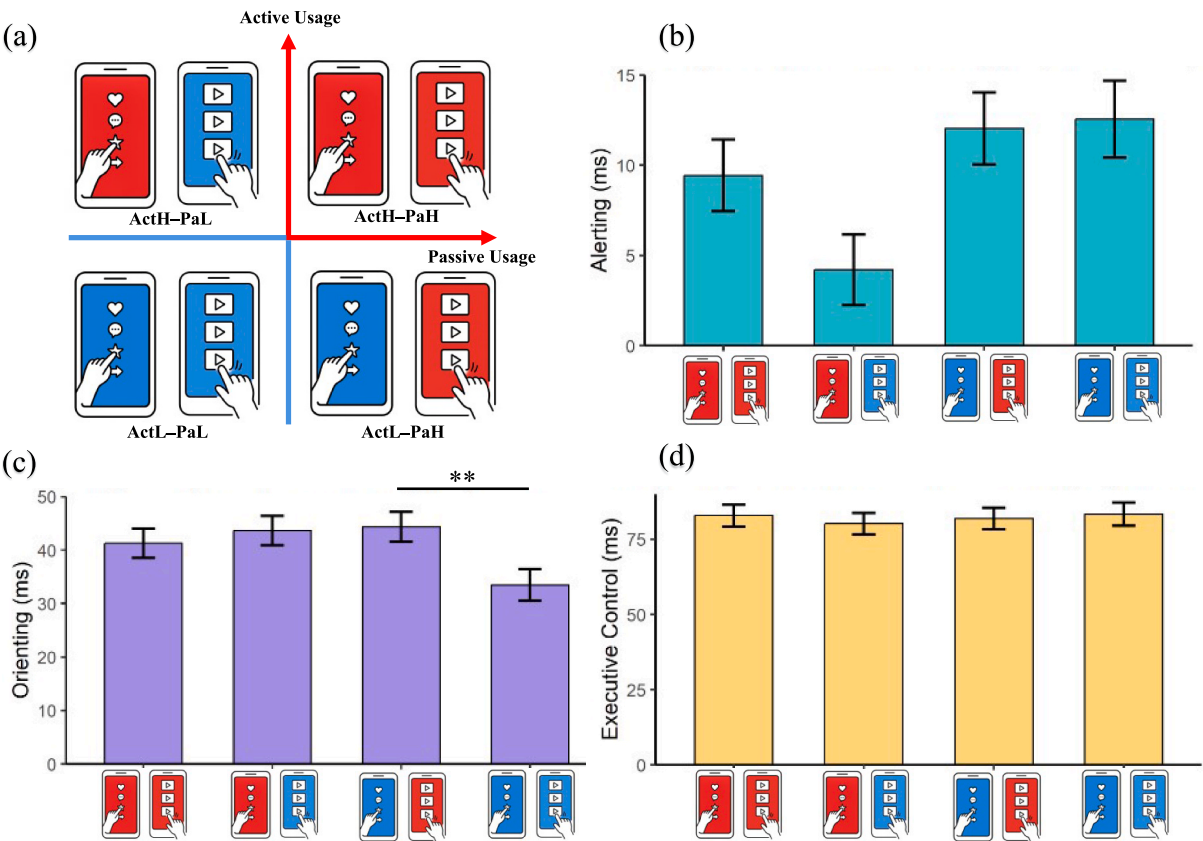


Fig. 3. Group differences in ANT efficiencies by Active \times Passive short video usage. Panels show mean efficiency (ms) for (a) Alerting [$RT_{(no\ cue)} - RT_{(center\ cue)}$], (b) Orienting [$RT_{(center\ cue)} - RT_{(spatial\ cue)}$], and (c) Executive control [$RT_{(incongruent)} - RT_{(congruent)}$] across four cohorts: ActH-PaH ($n = 83$), ActH-PaL ($n = 83$), ActL-PaH ($n = 79$), and ActL-PaL ($n = 74$). Error bars denote $\pm SE$. **: $p < 0.01$.

showed no signs of heteroscedasticity. Multicollinearity was assessed using tolerance and variance inflation factor (VIF) values, with tolerance > 0.10 and VIF < 5 indicating acceptable levels; all predictors met these criteria. Cases not meeting the criteria for outliers, leverage, or influential points were removed prior to the final analysis. The normal P-P plot indicated that residuals were approximately normally distributed.

As shown in Table 1, the results revealed that only active usage negatively predicted alerting ($\beta = -0.14, t = -2.58, p = 0.01$). The predictive effects of age, gender, and SVA were not significant, while testing locations positively predicted the alerting efficiency. Details of the other models are provided in Section S3.

Table 1

The hierarchical regression results for active and passive usage predicting alerting efficiency ($n = 319$).

Outcome Variable	Predictor Variable	R	R ²	F	β	t
alerting	gender	0.30	0.09	7.97***	-0.04	-0.78
	age				-0.03	-0.45
	SVA				-0.04	-0.65
	testing				0.29	5.18***
	locations					
alerting	gender	0.34	0.12	6.85***	-0.03	-0.45
	age				-0.04	-0.77
	SVA				-0.02	-0.26
	testing				0.29	5.06***
	locations					
	active usage				-0.14	-2.58**
	passive usage				0.07	1.23

Notes: In testing locations, “1 = offline test” and “0 = online test”. ***: $p < 0.001$. **: $p < 0.01$.

2.3. Discussion of experiment 1

In a large behavioral sample ($n = 319$), frequent active usage was reliably associated with reduced alerting efficiency, whereas orienting showed only a small group effect that did not survive hierarchical regression, and executive control exhibited no robust association. These results converged across our group-based comparisons and covariate-adjusted models, and they were not explained by speed-accuracy trade-offs, as error and omission outcomes did not mirror the alerting pattern. Together, the evidence localizes the primary behavioral correlate of short video habits to the alerting component of attention, with weaker or null relations for orienting and executive control after adjustment.

The alerting network indexes phasic readiness. In the ANT, a temporally informative warning cue transiently shifts the system from a resting baseline toward a preparatory state, yielding faster responses even though no additional target information is provided (Petersen and Posner, 2012; Hao et al., 2015). Our finding that heavier active usage predicts a smaller cue benefit is consistent with accounts in which concurrent or rapidly alternating goals erode tonic vigilance and the capacity to exploit brief warning signals. Active usage often entails social interaction while viewing, such as liking and commenting, or rapid switching between these behaviors and content consumption. This pattern resembles media multitasking, which divides attention across tasks and has been linked to more frequent lapses, mind-wandering, and reduced sustained attention (Shin et al., 2024; Madore et al., 2020; Ophir et al., 2009). Resource-control perspectives accordingly predict that when sustained attention is strained, the transient benefit conferred by a warning cue should diminish, manifesting as lower alerting efficiency (Huang et al., 2023).

The Active \times Passive interaction for orienting indicates that higher

passive usage was associated with greater orienting efficiency only among low-active users ($\text{ActL-PaH} > \text{ActL-PaL}$), whereas passive usage conferred no orienting advantage at high-active levels. One interpretation is that passive viewing exposes users to rapid, spatially localized transients that can tune exogenous orienting mechanisms, paralleling advantages observed in action video game research across sensory modalities (Mancarella et al., 2022; Wu et al., 2021). Mechanistically, this would fit with accounts in which the dorsal/ventral attention system and right TPJ support stimulus-driven reorienting to spatial cues (Petersen and Posner, 2012; Xuan et al., 2016). By contrast, high active usage adds social-cognitive demands (e.g., interpreting intentions, planning responses) and encourages frequent task-switching, conditions linked to reduced orienting or greater lapses under media multitasking (Ophir et al., 2009; Wu and Cheng, 2019). Taken together, the pattern suggests that passive usage may modestly facilitate spatial selection when interactive load is low, but that heavy active engagement may attenuate this benefit, yielding the interaction observed.

Converging evidence from independent paradigms supports this interpretation. Using an oddball task sensitive to phasic attentional allocation, Walla and Zheng (2024) reported reduced P300 amplitudes in high-intensity short video users, consistent with attenuated allocation of processing resources to salient events. Although their design did not isolate usage modes, the pattern aligns with our observation that active usage, rather than passive usage, is the primary behavioral correlate of reduced alerting. At the same time, our results remain correlational, and alternative explanations cannot be fully excluded. For example, individuals with lower baseline alerting might preferentially engage in more interactive platform features. We mitigated several confounds by controlling for short video addiction severity, age, gender, and testing location, yet causal direction cannot be established from cross-sectional data.

In sum, Experiment 1 identifies a selective link between active usage and diminished alerting efficiency, with limited and inconsistent evidence for orienting and no reliable association with executive control. This behavioral selectivity motivates a mechanistic test in Experiment 2 that focuses on intrinsic connectivity patterns at rest and evaluates whether specific connections within and between attention-related and default-mode systems mediate the active-usage–alerting association.

3. Experiment 2: neural mechanisms of short video usage and attention networks

Active usage is closely tied to social interaction and engages circuits encompassing the striatum (Sherman et al., 2018a), the TP (Herlin et al., 2021), and the bilateral TPJ (Lattanzio et al., 2021). In contrast, the alerting network is predominantly right-lateralized and involves the thalamus and frontal cortex (Petersen and Posner, 2012; Hao et al., 2015). To probe the neural basis of the behavioral association observed in Experiment 1, Experiment 2 used resting-state fMRI with brain-network analyses to test whether intrinsic functional connectivity mediates the link between active usage and reduced alerting efficiency. We hypothesized that the mediating pathways would involve coupling among nodes implicated in alerting (right thalamus and right frontal regions) and regions recruited by active usage (striatum, TP, and bilateral TPJ).

3.1. Methods and materials

3.1.1. Participants

The 115 offline participants from Experiment 1 (48 males; Mean age = 20.50, SD = 1.94) completed the questionnaires, behavioral testing, and an additional resting-state fMRI scanning.

3.1.2. MRI data acquisition

Whole-brain imaging data were gathered using a Siemens 3T Prisma scanner equipped with a 64-channel head coil at the Center for MRI

Research. Participants lay on their backs in the scanner, with foam pads used to minimize head movement. Before the scan, they were advised to keep their heads still and stay awake during the procedure. During the resting-state scan, participants were asked to keep their eyes open and refrain from engaging in systematic thought.

T1-weighted whole-brain structural images were acquired using a 3D magnetization-prepared rapid acquisition gradient echo sequence, with the following parameters: repetition time (TR) = 2530 ms, echo time (TE) = 2.98 ms, flip angle (FA) = 7°, slice thickness = 1 mm with no gap, field of view (FOV) = 256 mm × 256 mm², matrix = 256 × 256, and voxel size = 1 × 1 × 1 mm³.

The T2-weighted functional images were acquired using a gradient-echo planar imaging sequence with the following parameters: TR = 2000 ms, TE = 30 ms, FA = 90°, slice thickness = 2 mm with no gap, FOV = 224 mm × 224 mm², matrix = 112 × 112, voxel size = 2 mm × 2 mm × 2 mm³, and 62 slices.

3.1.3. rs-fMRI processing

Resting-state functional imaging data were preprocessed using the Data Processing Assistant for Resting-State fMRI (DPARSF, Yan, 2010). The first 10 time points were removed, and all functional images were adjusted to the acquisition time of the middle slice. The remaining functional images underwent head motion correction. Subjects with a maximum absolute head motion exceeding 3 mm or 3°, as well as those with an average framewise displacement greater than 0.2 mm, were excluded, resulting in the removal of 7 participants. Structural images were then segmented and registered to the MNI standard space using the ANTS registration method, with functional images resampled to a voxel size of 3 × 3 × 3 mm³. Following this, noise was removed using the ICA-AROMA's non-aggressive method. Head motion parameters, including the Friston 24-parameter model, were regressed out, and white matter and cerebrospinal fluid were included as covariates to reduce physiological noise. Linear trends were subsequently removed, and a 0.01–0.08 Hz band-pass filter was applied to reduce low-frequency drift and high-frequency noise. Gaussian smoothing was then performed with a full width at half maximum of 6 mm. Finally, time series data from specific brain regions were extracted.

After preprocessing, we used DPABI-Net (Yan et al., 2024) to construct functional networks and perform subsequent calculations. We computed the correlations between each pair of ROIs and transformed them into z-scores to enhance normality. This study utilized the 100-ROI parcellation based on the Yeo 17-network, as defined by Schaefer et al. (2018). The Yeo network template has been extensively used in multiple independent studies, showing a high level of reproducibility and consistency in functional parcellation (Liu et al., 2024; Yang et al., 2024). Because this template is derived from functional rather than structural connectivity, it more accurately represents the brain's functional distribution.

3.1.4. Statistical analyses

The preprocessing of behavioral data and the assumption testing procedures were identical to those described in Experiment 1. We conducted hierarchical regression analyses with 115 participants to predict the three sub-networks of the ANT. Six models were constructed: for each ANT sub-network (alerting, orienting, and executive control), gender, age, and SVA were entered at Step 1, followed by either active usage scores or passive usage scores at Step 2.

For the fMRI data, seven participants were excluded due to excessive head movement, leaving 108 valid participants. We conducted subsequent statistical analyses on the 4950 functional connectivities among 100 brain regions. Each functional connectivity was set as the dependent variable, active usage scores as the independent variable, and age, gender, SVA, and mean framewise displacement (mean FD, calculated using the Power method; Power et al., 2012) as covariates, to construct a multiple regression model. NBS correction was applied with edge $p < 0.001$ and component $p < 0.05$.

Subsequently, path analysis was conducted using the macro PROCESS (version 4.0) in IBM SPSS 27.0.1.0 (Hayes, 2013). Active usage scores were set as the independent variable, each corrected functional connectivity pair as the mediator, and RT in the ANT's alerting network as the dependent variable, with gender, age, SVA, and head motion (mean FD) as covariates. After standardizing the variables, Model 4 was used to test the mediation effects with the Bootstrap method.

3.2. Results

3.2.1. Behavioral results

In the results of the hierarchical regression, it was found that only active usage negatively predicted the alerting efficiency (Table 2). For other results, please refer to Table S4–S5. Specifically, age, gender, and SVA, which were included initially, did not predict the alerting efficiency. When active usage was added, it significantly predicted the alerting efficiency ($\beta = -0.29, t = -2.90, p = 0.005$). The models met the assumptions of hierarchical regression.

3.2.2. Functional connectivity and mediation model results

A multiple regression model was established to examine the relationship between active short video usage and functional connectivity within brain networks. Fig. 4a displays the NBS-corrected functional connections, showing that active usage involved the limbic network, control network, and salience & ventral attention network, but the results were primarily within the default network. Detailed information for each functional connectivity is available in supplementary materials in Table S6.

As shown in Fig. 4b, the number of these functional connectivities across different networks is displayed. DefaultA and DefaultB had the most inter-network functional connections, with DefaultB having the highest number of connections with other networks.

The mediation effect of functional connectivity between active usage and alerting efficiency was tested using Model 4 of the PROCESS written by Hayes (2013). Covariates included the SVA, gender, age, and mean FD. The path diagram of active usage to alerting efficiency is presented in Fig. 4c. The direct predictive effect of active usage on alerting efficiency was significant ($\beta = -0.271, t = -2.60, p = 0.011$). When the mediating variable of functional connectivity (right ventral prefrontal cortex and right posterior cingulate, R.PFCv1-R.Cingp1) was included, this direct effect was not significant ($\beta = -0.200, t = -1.84, p = 0.068$).

3.3. Discussion of experiment 2

Experiment 2 isolates an intrinsic, right-lateralized control–default coupling, specifically, PFCv to PCC (atlas label ‘Cingp’), that statistically mediates the association between active usage and reduced alerting efficiency, aligning with right-hemisphere models of alerting (Petersen and Posner, 2012; Hao et al., 2015). This effect was selective to active usage and did not extend to orienting or executive control, nor did

Table 2
The hierarchical regression results for active usage and the alerting efficiency (n = 115).

Outcome Variable	Predictor Variable	R	R ²	F	β	t
Alerting		0.13	0.02	0.61		
	gender				0	0.01
	age				0.12	1.27
	SVA				0.06	0.66
Alerting		0.29	0.09	2.60*		
	gender				0.01	0.02
	age				0.08	0.86
	SVA				0.17	1.70
	active usage				-0.29	-2.90**

Note: SVA = the Short Video Addiction score. **: $p < 0.01$, *: $p < 0.05$.

passive usage show comparable mediation, consistent with task-based evidence that socially contingent behaviors recruit distinct circuitry (Sherman et al., 2018a, 2018b).

Notably, candidate mediators in social-reward and person-knowledge regions (striatum, TP, bilateral TPJ) did not survive correction, suggesting that the resting-state signature of active usage relates more to baseline readiness at the control–default interface than to stimulus-locked social appraisal (Faskowitz et al., 2022; Lv et al., 2018; Suarez et al., 2020). While cross-sectional mediation cannot establish causality, the pathway was robust to covariates, offering a compact mechanistic account that complements the behavioral selectivity observed in Experiment 1.

Experiment 2 found that active short video usage corresponded to a specific brain network, which may be related to interpersonal interaction behaviors in the virtual world. Additionally, the functional connectivity between the right PFCv and the right PCC served as a mediator for predicting the alerting network based on active usage. We speculated that these two brain regions may be associated with the allocation of attentional resources during active usage.

4. General discussion

This study provides convergent behavioral and neuroimaging evidence that active short video usage, as distinct from passive usage, is selectively associated with diminished alerting efficiency and a right-lateralized intrinsic pathway linking control and DMN. In a two-experiment design (n = 319 behavioral; n = 115 fMRI), active usage consistently predicted lower alerting efficiency. Resting-state analyses identified a PFCv and PCC coupling in the right hemisphere that statistically mediated the link between active-usage and alerting, with specificity to active usage and robustness to covariates (addiction severity, age, gender, testing location). Network mapping indicated contributions from the default mode, salience/ventral attention, and limbic systems, but the critical mediator localized to a control-DMN interface, pinpointing a modifiable resting-state signature of reduced phasic readiness. Methodologically, the work advances the field by operationalizing active versus passive usage, aligning ANT subnetwork indices with intrinsic connectivity, and moving beyond task-evoked designs to a mechanistic account at rest. Conceptually, it extends resource-control perspectives to interactive short-video contexts and delivers actionable neural metrics for future intervention, design, and policy discussions around digital attention health.

4.1. Complementary roles of the DMN and salience/ventral attention systems in active usage

Active short video usage appears to recruit the DMN and the Salience/Ventral Attention Network in complementary ways, with partially distinct computational roles. Within the DMN, the PFCm, PCC, TPJ, and TP work together to attach self- and social-meaning to incoming content. Task-based fMRI using social-feedback paradigms shows that interactive behaviors such as giving or receiving Likes co-activate MPFC with valuation circuitry in a manner consistent with appraisal and reinforcement during engagement (Sherman et al., 2018a, 2018b). Personalized-stream designs further indicate that recommended clips recruit DMN nodes and modulate their coupling with attention/-control systems, suggesting that external narratives are aligned with ongoing internal mentation (Su et al., 2021a, 2021b). Meta-analytic and synthesis work assigns self-referential evaluation and self-related memory to an PFCm-PCC-TPJ circuit (Frewen et al., 2020), while the TP contributes person knowledge and affective meaning that shape how characters and scenes are interpreted (Herlin et al., 2021). Developmental and functional accounts also link ventral prefrontal regions to social flexibility and the regulation of socio-emotional behavior, providing a route by which appraisals inform subsequent interactive choices (Nelson and Guyer, 2011).

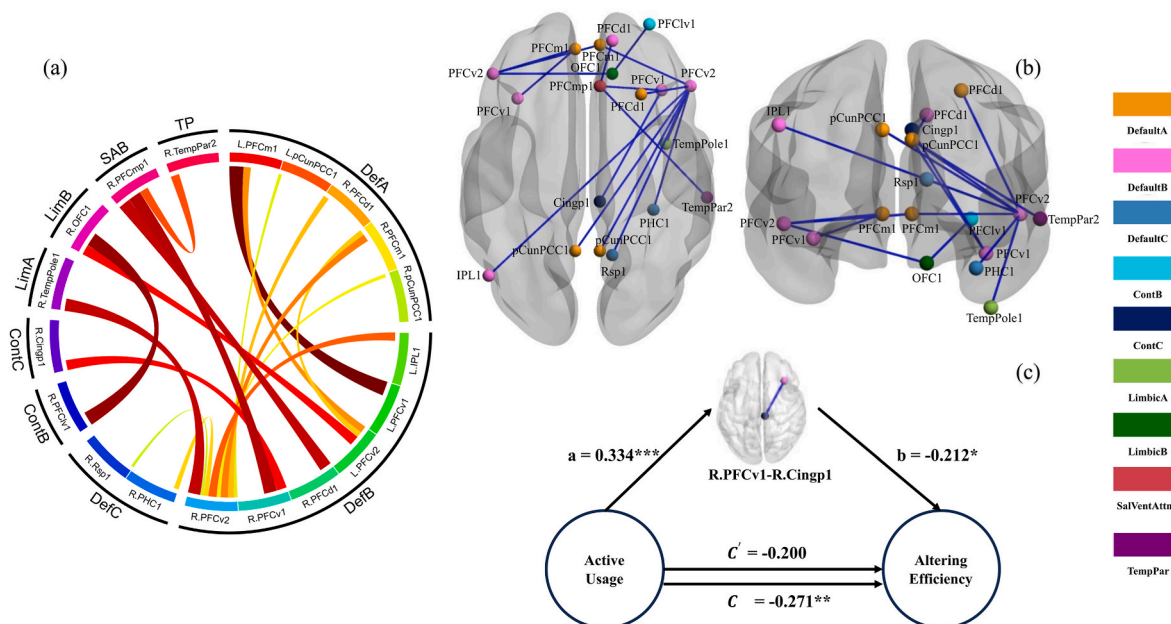


Fig. 4. Functional connectivity of active short video usage and mediation of alerting efficiency. (a): Functional connections significantly predicted by active usage, with effects spanning limbic, control, and salience/ventral-attention networks and concentrated within the default network. (b): NBS-corrected node locations significantly predicted by active usage. Network counts highlight DefaultA and DefaultB as the most connected in inter-network links. (c): Mediation model linking active usage to reduced alerting efficiency via resting-state functional connectivity between right ventral prefrontal cortex and right posterior cingulate (R.PFCv1-R.Cingp1), controlling for SVA, gender, age, and head motion (mean FD). Abbreviations: PFCm, medial prefrontal cortex; PFCv, ventral prefrontal cortex; PFCd, dorsal prefrontal cortex; PHC, parahippocampal cortex; Rsp, retrosplenial cortex; PFCvl, lateral ventral prefrontal cortex; TempPar, temporal-parietal; pCunPCC, pre-cuneus/posterior cingulate cortex; IPL, inferior parietal lobule; TempPole, temporal pole; PFCmp, medial posterior prefrontal cortex; Cingp, posterior cingulate; OFC, orbitofrontal cortex.

By contrast, the Salience/Ventral Attention Network prioritizes behaviorally relevant cues and supports rapid reorienting when important changes occur. Ventral frontal regions, including PFCv and OFC, integrate affective value with current goals, thereby gating attention toward salient signals and shaping approach-avoidance tendencies. The right TPJ contributes to stimulus-driven reorienting and decoding of social cues that demand immediate action or evaluation. Experimental evidence illustrates how brief, emotionally charged, multisensory experiences can transiently amplify salience-network engagement and feed-forward perception-action processing (Franceschini et al., 2024), a pattern that helps explain why short, dynamic clips can momentarily bias attentional set even in the absence of explicit task demands. In our context, these salience operations likely determine which segments of the stream capture attention and trigger interaction, while DMN processes supply the self- and social-meaning that guide what the user chooses to do next.

Interestingly, several of these processes show right-hemisphere biases, which aligns with the lateralization observed in our intrinsic connectivity results. Theory-of-Mind operations, including belief and intention inference, are often stronger in right-lateralized TPJ-prefrontal circuits (Masina et al., 2022). Clinical and neuropsychological syntheses implicate the right hemisphere in empathy and emotion recognition, as well as in broader social-emotional communication (Mesulam, 2023). Self-referential functions within MPFC-PCC-TPJ likewise show asymmetries that can favor right-hemisphere hubs depending on task demands (Frewen et al., 2020). Together, these literatures provide a convergent framework: DMN nodes construct self and social meaning that sustain interactive behavior, the Salience/Ventral Attention Network triages and reorients to moment-to-moment significance, and right-hemisphere specializations help explain the lateralized coupling associated with active usage in our data.

4.2. Active usage diminishes alerting via right PFCv-PCC coupling

Active usage negatively predicted alerting efficiency, and this relationship was statistically mediated by intrinsic coupling between the right PFCv and the right PCC. Framed by the resource-control account, attentional capacity is limited and must be apportioned across concurrent demands (Huang et al., 2023). Short-video browsing itself consumes resources for continuous audiovisual parsing; highly active users additionally allocate resources to social interpretation and response selection (e.g., inferring others’ intentions, choosing whether and how to reply). This concurrent or rapidly alternating allocation provides a plausible route to diminished phasic readiness when a brief warning signal appears.

Neurocognitively, the ventral attention network, with PFCv as a key node, supports rapid reorienting to salient, unexpected events and facilitates task switching under distraction (Tosoni et al., 2023). The PCC contributes not only to self-referential processing but also to balancing internal and external attention, dynamically redistributing resources as task demands shift (Leech and Sharp, 2014). The observed PFCv-PCC mediation therefore points to a control-default interface at rest that indexes how resources are poised between social/internal mentation and readiness for external signals; in our data, variation in this coupling accounted for the link between active usage and lower alerting benefits.

This interpretation aligns with evidence that sustained attention degrades under divided goals, increasing mind-wandering and attentional lapses (Madore et al., 2020; Shin et al., 2024). Because alerting reflects a tonic-phasic readiness to respond to sudden stimuli (Fan et al., 2009), any shift of resources away from externally oriented preparedness, whether due to simultaneous social appraisal or frequent switching, will blunt cue benefits. In summary, active users appear to distribute attention across social and perceptual demands in ways that bias the PFCv-PCC system toward internal/social processing, which in turn manifests behaviorally as reduced alerting efficiency.

4.3. Contribution, age constraints, and future directions

Across a behavioral cohort and an rs-fMRI cohort, we find that active usage selectively predicts reduced alerting efficiency, with a right PFCv and PCC coupling mediating this link. This finding indicates that alerting in attention is most vulnerable in the short-video context and a right-lateralized control-DMN connectivity advance resource-control accounts beyond task-evoked evidence to a mechanistic resting-state pathway. In addition, the present study operationalizes active vs. passive usage and aligns ANT subnetwork indices with intrinsic connectivity, yielding actionable neural and behavioral markers for intervention, platform design, and policy aimed at mitigating digital attention costs.

Notably, the relatively small proportion of variance explained by our regression models ($R^2 = .09$) suggests that key sources of between-participant heterogeneity were under-represented. Age is a well-established determinant of alerting efficiency (Kaufman et al., 2016; Williams et al., 2016; Zhou et al., 2011), yet our sample comprised young adults within a narrow range. Such restriction of range limits the observable covariance between age and alerting, which can suppress model fit and attenuate associations among the other predictors. Prior work indicates that alerting changes across the lifespan, with developmental improvements through adolescence and young adulthood and declines with advancing age; these trends likely reflect age-sensitive differences in baseline arousal, phasic readiness, and the efficiency of networks supporting alerting (Kaufman et al., 2016; Williams et al., 2016; Zhou et al., 2011). In a young-adult only cohort, variance in these age-linked factors is compressed, which may both lower R^2 and obscure potential Age \times Usage interactions relevant to alerting. Future studies should recruit across a broader age spectrum and more diverse demographics, model nonlinear age effects, and explicitly test whether age moderates the relation between usage patterns and attention sub-networks.

Looking forward, we recommend broadening sampling across the lifespan and socio-demographic strata; modeling nonlinear age effects and explicit moderation by age; and enriching covariates that plausibly shape attention (sleep, circadian timing, affect, trait impulsivity, device context) alongside addiction severity. Measurement should move beyond self-report with digital-trace logs of active usage and passive usage, coupled with ecological momentary assessment to capture state fluctuations in attention. Design-wise, longitudinal experiments (e.g., controlled reductions or structured boosts of active features) can address directionality, while within-subject crossover and time-series approaches can test short-term carryover to alerting. On the neural side, complement static resting-state connectivity with dynamic functional connectivity, effective connectivity, and network-control or mediation models that test pathway specificity and generalize via cross-validation. Finally, replication in culturally diverse cohorts and translation into targeted interventions (e.g., interface designs that throttle high-frequency interactive prompts, time-structured engagement, or attentional readiness training) will be essential to evaluate real-world impact and boundary conditions for the selective association between active short video usage and reduced alerting.

CRedit authorship contribution statement

Guanghui Zhai: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Conceptualization. **Yang Feng:** Validation, Methodology, Conceptualization. **Xin Ling:** Writing – review & editing, Validation, Methodology. **Jiahui Su:** Writing – review & editing, Validation, Investigation, Conceptualization. **Yifan Liu:** Methodology, Data curation. **Yiwei Li:** Methodology, Data curation. **Yunpeng Jiang:** Writing – review & editing, Software, Resources, Methodology, Funding acquisition, Data curation, Conceptualization. **Xia Wu:** Writing – review & editing, Validation, Supervision, Resources, Project administration,

Methodology, Funding acquisition, Data curation, Conceptualization.

Informed consent statement

Informed consent was obtained from all subjects involved in the study.

Institutional review board statement

The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of Tianjin Normal University (No. 2025030311, 3 March 2025).

Institutional review board statement

The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of Tianjin Normal University (No. 2022030702, 4 March 2022).

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Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.neuropsychologia.2025.109291>.

Data availability

Because of the large size of the nuclear magnetic data, it is inconvenient to provide.

References

- Afra, E., Janszky, J., Perlaki, G., Orsi, G., Nagy, S.A., Arato, A., Szente, A., Alhour, H.A. M., Kis-Jakab, G., Darnai, G., 2023. Altered functional brain networks in problematic smartphone and social media use: resting-state fMRI study. *Brain Imaging and Behavior* 292–301. <https://doi.org/10.1007/s11682-023-00825-y>.
- Bertoni, S., Franceschini, S., Mancarella, M., Puccio, G., Ronconi, L., Marsicano, G., Gori, S., Campana, G., Facchetti, A., 2024. Action video games and posterior parietal cortex neuromodulation enhance both attention and reading in adults with developmental dyslexia. *Cerebr. Cortex* 34 (4), bhae152. <https://doi.org/10.1093/cercor/bhae152>.
- Bertoni, S., Franceschini, S., Puccio, G., Mancarella, M., Gori, S., Facchetti, A., 2021. Action video games enhance attentional control and phonological decoding in children with developmental dyslexia. *Brain Sci.* 11 (2), 171. <https://doi.org/10.3390/brainsci11020171>.
- Blanca, M., Alarcón, R., Arnau, J., Bono, R., Bendayan, R., 2017. Non-normal data: is ANOVA still a valid option? *Psicothema* 4 (29), 552–557. <https://doi.org/10.7334/psicothema2016.383>.
- Chao, M., Lei, J., He, R., Jiang, Y., Yang, H., 2023. TikTok use and psychosocial factors among adolescents: comparisons of non-users, moderate users, and addictive users. *Psychiatry Res.* 325, 115247. <https://doi.org/10.1016/j.psychres.2023.115247>.
- Chen, G., Gao, X., Yan, X., Du, M., Zang, Y., Wang, Y., 2023. Online research in psychology and its future in China. *Journal of Psychological Science* 46 (5), 1262–1271. <https://doi.org/10.16719/j.cnki.1671-6981.20230529>.
- De Souza Almeida, R., Faria-Jr, A., Klein, R.M., 2021. On the origins and evolution of the attention network tests. *Neurosci. Biobehav. Rev.* 126, 560–572. <https://doi.org/10.1016/j.neubiorev.2021.02.028>.

- Fan, J., Gu, X., Guise, K.G., Liu, X., Fossella, J., Wang, H., Posner, M.I., 2009. Testing the behavioral interaction and integration of attentional networks. *Brain Cognit.* 70 (2), 209–220. <https://doi.org/10.1016/j.bandc.2009.02.002>.
- Fan, J., McCandliss, B.D., Sommer, T., Raz, A., Posner, M.I., 2002. Testing the efficiency and Independence of attentional networks. *J. Cognit. Neurosci.* 14 (3), 340–347. <https://doi.org/10.1162/0899892002317361886>.
- Faskowitz, J., Betzel, R.F., Sporns, O., 2022. Edges in brain networks: contributions to models of structure and function. *Network Neuroscience* 6 (1), 1–28. https://doi.org/10.1162/netn_a.00204.
- Franceschini, S., Puccio, G., Bertoni, S., Gori, S., Mascheretti, S., Fusina, F., Angrilli, A., Facchetti, A., 2024. The benefits of playing action-like video games on salience processing. *Int. J. Hum. Comput. Interact.* 1–14. <https://doi.org/10.1080/10447318.2024.2346693>.
- Frewen, P., Schroeter, M.L., Riva, G., Cipresso, P., Fairfield, B., Padulo, C., Kemp, A.H., Palaniyappan, L., Owolabi, M., Kusi-Mensah, K., Polyakova, M., Fehertoi, N., D'Andrea, W., Lowe, L., Northoff, G., 2020. Neuroimaging the consciousness of self: review, and conceptual-methodological framework. *Neurosci. Biobehav. Rev.* 112, 164–212. <https://doi.org/10.1016/j.neubiorev.2020.01.023>.
- Fu, J., Xu, P., Zhao, L., Yu, G., 2018. Impaired orienting in youth with internet addiction: evidence from the attention network task (ANT). *Psychiatry Res.* 264, 54–57. <https://doi.org/10.1016/j.psychres.2017.11.071>.
- Guo, Y., Elhai, J.D., Montag, C., Wang, Y., Yang, H., 2024. Problematic mobile gamers have attention bias toward game social information. *Comput. Hum. Behav.* 152, 108074. <https://doi.org/10.1016/j.chb.2023.108074>.
- Hao, L., Sang, N., Du, X., Qiu, J., Wei, D., Chen, X., 2015. Examining brain structures associated with attention networks in a large sample of young adults: a voxel-based morphometry study. *Science Bulletin* 60 (21), 1824–1832. <https://doi.org/10.1007/s11434-015-0910-0>.
- Hayes, A.F., 2013. *Introduction to Mediation, Moderation, and Conditional Process Analysis: a Regression-based Approach*. The Guilford Press.
- Herlin, B., Navarro, V., Dupont, S., 2021. The temporal pole: from anatomy to function-A literature appraisal. *J. Chem. Neuroanat.* 113, 101925. <https://doi.org/10.1016/j.jchemneu.2021.101925>.
- Huang, H., Li, R., Zhang, J., 2023. A review of visual sustained attention: neural mechanisms and computational models. *PeerJ* 11, e15351. <https://doi.org/10.7717/peerj.15351>.
- Johnson, K.A., Robertson, I.H., Barry, E., Mulligan, A., Daibhis, A., Daly, M., Watchorn, A., Gill, M., Bellgrove, M.A., 2008. Impaired conflict resolution and alerting in children with ADHD: evidence from the Attention network task (ANT). *JCPP (J. Child Psychol. Psychiatry)* 49 (12), 1339–1347. <https://doi.org/10.1111/j.1469-7610.2008.01936.x>.
- Kaufman, D.A.S., Szoda, C.N., Dotson, V.M., Perlstein, W.M., 2016. An event-related potential investigation of the effects of age on alerting, orienting, and executive function. *Front. Aging Neurosci.* 8, 99. <https://doi.org/10.3389/fnagi.2016.00099>.
- Lattanzio, L., Seames, A., Holden, S.K., Buard, I., 2021. The emergent relationship between temporoparietal junction and anosognosia in Alzheimer's disease. *J. Neurosci. Res.* 99 (9), 2091–2096. <https://doi.org/10.1002/jnr.24904>.
- Leech, R., Sharp, D.J., 2014. The role of the posterior cingulate cortex in cognition and disease. *Brain* 137 (1), 12–32. <https://doi.org/10.1093/brain/awt162>.
- Li, Z., 2016. Psychological empowerment on social media: who are the empowered users? *Public Relat. Rev.* 42 (1), 49–59. <https://doi.org/10.1016/j.pubrev.2015.09.001>.
- Liao, M., 2024. Analysis of the causes, psychological mechanisms, and coping strategies of short video addiction in China. *Front. Psychol.* 15, 1391204. <https://doi.org/10.3389/fpsyg.2024.1391204>.
- Liu, J., Cui, W., Chen, Y., Ma, Y., Dong, Q., Cai, R., Li, Y., Hu, B., 2024. Deep fusion of multi-template using spatio-temporal weighted multi-hypergraph convolutions networks for brain disease analysis. *IEEE Trans. Med. Imag.* 43 (2), 860–873. <https://doi.org/10.1109/TMI.2023.3325261>.
- Lv, H., Wang, Z., Tong, E., Williams, L.M., Zaharchuk, G., Zeineh, M., Goldstein-Piekarski, A.N., Ball, T.M., Liao, C., Wintermark, M., 2018. Resting-state functional MRI: everything that nonexperts have always wanted to know. *Am. J. Neuroradiol.* <https://doi.org/10.3174/ajnr.A5527> ajnr.ajnr.A5527v1.
- Madore, K.P., Khazenzon, A.M., Backes, C.W., Jiang, J., Uncapher, M.R., Norcia, A.M., Wagner, A.D., 2020. Memory failure predicted by attention lapsing and media multitasking. *Nature* 587 (7832), 87+. <https://doi.org/10.1038/s41586-020-2870-z>.
- Mancarella, M., Antzaka, A., Bertoni, S., Facchetti, A., Lallier, M., 2022. Enhanced disengagement of auditory attention and phonological skills in action video gamers. *Comput. Hum. Behav.* 135, 107344. <https://doi.org/10.1016/j.chb.2022.107344>.
- Masina, F., Pezzetta, R., Lago, S., Mantini, D., Scarpazza, C., Arcara, G., 2022. Disconnection from prediction: a systematic review on the role of right temporoparietal junction in aberrant predictive processing. *Neurosci. Biobehav. Rev.* 138, 104713. <https://doi.org/10.1016/j.neubiorev.2022.104713>.
- Mesulam, M.-M., 2023. Temporopolar regions of the human brain. *Brain : J. Neurol.* 146 (1), 20–41. <https://doi.org/10.1093/brain/awac339>.
- Nelson, E.E., Guyer, A.E., 2011. The development of the ventral prefrontal cortex and social flexibility. *Developmental Cognitive Neuroscience* 1 (3), 233–245. <https://doi.org/10.1016/j.dcn.2011.01.002>.
- Ophir, E., Nass, C., Wagner, A.D., 2009. Cognitive control in media multitaskers. *Proc. Natl. Acad. Sci.* 106 (37), 15583–15587. <https://doi.org/10.1073/pnas.0903620106>.
- Petersen, S.E., Posner, M.I., 2012. The attention system of the human brain: 20 years after. <https://doi.org/10.1146/annurev-neuro-062111-150525>.
- Power, J.D., Barnes, K.A., Snyder, A.Z., Schlaggar, B.L., Petersen, S.E., 2012. Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. *Neuroimage* 59 (3), 2142–2154. <https://doi.org/10.1016/j.neuroimage.2011.10.018>.
- Schaefer, A., Kong, R., Gordon, E.M., Laumann, T.O., Zuo, X.-N., Holmes, A.J., Eickhoff, S.B., Yeo, B.T.T., 2018. Local-global parcellation of the human cerebral cortex from intrinsic functional connectivity MRI. *Cerebr. Cortex* 28 (9), 3095–3114. <https://doi.org/10.1093/cercor/bhx179>.
- Sherman, L., Greenfield, P., Hernandez, L., Dapretto, M., 2018a. Peer influence via Instagram: effects on brain and behavior in adolescence and young adulthood. *Child Dev.* 89 (1), 37–47. <https://doi.org/10.1111/cdev.12838>.
- Sherman, L., Hernandez, L., Greenfield, P., Dapretto, M., 2018b. What the brain “Likes”: neural correlates of providing feedback on social media. *Soc. Cognit. Affect Neurosci.* 13 (7), 699–707. <https://doi.org/10.1093/scan/nsy051>.
- Shin, M., Taseski, D., Murphy, K., 2024. Media multitasking is linked to attentional errors, mind wandering and automatised response to stimuli without full conscious processing. *Behav. Inf. Technol.* 43 (3), 445–457. <https://doi.org/10.1080/0144929X.2023.2167669>.
- Su, C., Zhou, H., Gong, L., Teng, B., Geng, F., Hu, Y., 2021a. Viewing personalized video clips recommended by TikTok activates default mode network and ventral tegmental area. *Neuroimage* 237. <https://doi.org/10.1016/j.neuroimage.2021.118136>.
- Su, C., Zhou, H., Wang, C., Geng, F., Hu, Y., 2021b. Individualized video recommendation modulates functional connectivity between large scale networks. *Hum. Brain Mapp.* 42 (16), 5288–5299. <https://doi.org/10.1002/hbm.25616>.
- Suarez, L.E., Markello, R.D., Betzel, R.F., Misis, B., 2020. Linking structure and function in macroscale brain networks. *Trends Cognit. Sci.* 24 (4), 302–315. <https://doi.org/10.1016/j.tics.2020.01.008>.
- Tosoni, A., Capotosto, P., Baldassarre, A., Spadone, S., Sestieri, C., 2023. Neuroimaging evidence supporting a dual-network architecture for the control of visuospatial attention in the human brain: a mini review. *Front. Hum. Neurosci.* 17 (28), 1250096. <https://doi.org/10.3389/fnhum.2023.1250096>.
- Verduyn, P., Gugushvili, N., Kross, E., 2022. Do social networking sites influence well-being? The extended active-passive model. *Curr. Dir. Psychol. Sci.* 31 (1), 62–68. <https://doi.org/10.1177/09637214211053637>.
- Wadley, M., Hsien, N., 2023. A systematic review of structural and functional MRI studies investigating social networking site use. *Brain Sci.* 13 (5), 1079. <https://doi.org/10.3390/brainsci13050787>.
- Walla, P., Zheng, Y., 2024. Intense short-video-based social media use reduces the P300 event-related potential component in a visual oddball experiment: a sign for reduced attention. *Life* 14 (3), 290. <https://doi.org/10.3390/life14030290>.
- Wang, B., Jiang, J., Guo, W., 2023. Effects of a single bout of mobile action video game play on attentional networks. *PeerJ* 11, e16409. <https://doi.org/10.7717/peerj.16409>.
- Williams, R.S., Biel, A.L., Wegier, P., Lapp, L.K., Dyson, B.J., Spaniol, J., 2016. Age differences in the attention network test: evidence from behavior and event-related potentials. *Brain Cognit.* 102, 65–79. <https://doi.org/10.1016/j.bandc.2015.12.007>.
- Wu, J., Cheng, T., 2019. Who is better adapted in learning online within the personal learning environment? Relating gender differences in cognitive attention networks to digital distraction. *Comput. Educ.* 128, 312–329. <https://doi.org/10.1016/j.compedu.2018.08.016>.
- Wu, X., Jiang, Y., Jiang, Y., Chen, G., Chen, Y., Bai, X., 2021. The influence of action video games on attentional functions across visual and auditory modalities. *Front. Psychol.* 12, 611778. <https://doi.org/10.3389/fpsyg.2021.611778>.
- Xuan, B., Mackie, M.-A., Spagna, A., Wu, T., Tian, Y., Hof, P.R., Fan, J., 2016. The activation of interactive attentional networks. *Neuroimage* 129, 308–319. <https://doi.org/10.1016/j.neuroimage.2016.01.017>.
- Yan, 2010. DPARSF: a MATLAB toolbox for “pipeline” data analysis of resting-state fMRI. *Front. Syst. Neurosci.* <https://doi.org/10.3389/fnys.2010.00013>.
- Yan, C., Wang, X., Lu, B., Deng, Z., Gao, Q., 2024. DPABINet: a toolbox for brain network and graph theoretical analyses. *Science Bulletin* 69 (11), 1628–1631. <https://doi.org/10.1016/j.scib.2024.02.038>.
- Yan, T., Su, C., Xue, W., Hu, Y., Zhou, H., 2024. Mobile phone short video use negatively impacts attention functions: an EEG study. *Front. Hum. Neurosci.* 18, 1383913. <https://doi.org/10.3389/fnhum.2024.1383913>.
- Yang, Y., Ye, C., Guo, X., Wu, T., Xiang, Y., Ma, T., 2024. Mapping multi-modal brain connectome for brain disorder diagnosis via cross-modal mutual learning. *IEEE Trans. Med. Imag.* 43 (1), 108–121. <https://doi.org/10.1109/TMI.2023.3294967>.
- Zeng, X., Han, X., Gao, F., Sun, Y., Yuan, Z., 2023. Abnormal structural alterations and disrupted functional connectivity in behavioral addiction: a meta-analysis of VBM and fMRI studies. *Journal of Behavioral Addictions* 12 (3), 599–612. <https://doi.org/10.1556/2006.2023.00025>.
- Zhai, G., Su, J., Chen, Z., Feng, Y., Jiang, Y., Liu, T., Wu, X., 2024. The relationships between short video usage and subjective well-being: mediation models and network analysis. *Behav. Sci.* 14 (11). <https://doi.org/10.3390/bs14111082>.
- Zhou, S., Fan, J., Lee, T.M.C., Wang, C., Wang, K., 2011. Age-related differences in attentional networks of alerting and executive control in young, middle-aged, and older Chinese adults. *Brain Cognit.* 75 (2), 205–210. <https://doi.org/10.1016/j.bandc.2010.12.003>.