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Digital Alzheimer's: A Descriptive-Integrative Framework for Cognitive Fragmentation in the Social Media Age

Linh Le Gia[1], Tu Tran Quang Vinh[2], Ha Nguyen Manh[3*]

[1]HNUE High School for Gifted Students, Hanoi, Vietnam.
Email: lglinh0812@gmail.com
[2]International Schools of North America, Ho Chi Minh City, Vietnam.
Email: alext1608sgs@gmail.com
[3]Truong Thanh Viet Nam Group, Vietnam (ORCID: 0009-0009-5373-3420)
Email: ha.nm1589@gmail.com
*Corresponding author

Abstract: *This cross-sectional, mixed-methods study examined associations between social media usage intensity and cognitive performance in 180 university students (M age = 21.7), categorized into Heavy (≥4 h/day, n = 62), Moderate (1–3 h/day, n = 71), and Light (<1 h/day, n = 47) groups. Heavier use was associated with lower performance across working memory (η^2p = .27), episodic memory (.32), sustained attention (.30), executive function (.25), and processing speed (.28). Hierarchical regression indicated 57% of variance in composite cognitive scores was associated with the full predictor set. A statistical indirect effect of cognitive offloading on the social media–memory association was observed (B = -0.26, 95% CI [-0.36, -0.17]). EEG findings showed elevated theta and suppressed alpha during scrolling in heavy users. A descriptive-integrative framework with three empirically supported tiers (Memory Offloading, Attentional Fragmentation, Shallow Processing Loop) and one hypothesized extension (Social-Cognitive Erosion) is proposed; the framework is descriptive rather than causal, pending longitudinal validation. Results reflect associations within a student sample; causal claims require longitudinal replication.*

Keywords: *Digital Alzheimer's, Cognitive Fragmentation, Social Media, Neuropsychological Assessment, EEG, Cognitive Offloading*

1. Introduction

The widespread adoption of social media has transformed information processing behavior across populations. Recent estimates suggest that the average young adult engages with social media for three to five hours daily (DataReportal, 2025), raising questions about possible associations with cognitive functioning. Clinicians and educators have reported observations of attentional difficulties, memory complaints, and reduced tolerance for sustained cognitive effort in young adults—patterns that warrant systematic investigation.

This study proposes "Digital Alzheimer's" as a descriptive, metaphorical framework—explicitly distinct from clinical Alzheimer's disease—for characterizing multi-domain cognitive performance differences associated with social media use intensity. The framework draws structural parallels to highlight that the observed profile spans multiple domains simultaneously, analogous to (though mechanistically unrelated to) early Alzheimer's. The study integrates neuropsychological testing, EEG, self-report measures, and qualitative interviews, while acknowledging that the cross-sectional design limits inference to associations.

Despite expanding literature on social media and cognition, three gaps motivate this study. First, most prior work has examined single cognitive domains (e.g., memory in Sparrow et al., 2011; attention in Mark, 2023) rather than multi-domain profiles. Second, EEG studies (e.g., Satani et al., 2025) have characterized neurophysiological signatures during social media use but have not been integrated with behavioral testing or qualitative accounts. Third, behavioral mechanisms (cognitive offloading, short-form content consumption) have rarely been tested alongside screen-time quantity as competing predictors.

Research Objectives and Questions

The objectives are: (a) to characterize multi-domain cognitive performance across social media use intensity groups; (b) to identify behavioral mechanisms (cognitive offloading, short-form content) that operate beyond screen-time quantity; (c) to triangulate behavioral, neurophysiological, and qualitative evidence; and (d) to propose a descriptive-integrative framework organizing these findings. Four research questions guide the analyses:

- How does cognitive performance vary across social media usage intensity groups across multiple domains (working memory, episodic memory, attention, executive function, processing speed)?
- Do cognitive offloading and short-form content consumption account for variance in cognitive performance beyond screen-time quantity?
- Do EEG signatures during scrolling (theta, alpha, gamma) differ by usage intensity in ways that converge with behavioral findings?
- Do participants' subjective accounts (qualitative interviews) converge with quantitative and neurophysiological patterns to support a multi-domain framework?

2. Literature review

Concern about how digital technology reshapes human cognition has developed across three largely separate research traditions—memory, attention, and neurophysiology—each with its own constructs, methods, and degree of empirical consensus. The following review synthesizes these strands, traces the evolution of their claims from broad alarm toward mechanistically specific and increasingly contested accounts, and motivates the integrative framework adopted in the present study.

The earliest and most sweeping claims concerned memory. Spitzer (2012) popularized the term "digital dementia" to describe a cognitive deterioration he attributed to excessive device use, a characterization that proved influential but remained diagnostic rather than mechanistic. Experimental research subsequently supplied a more precise account. Sparrow et al. (2011) demonstrated that participants who expected to retain future access to information encoded it less effectively, a phenomenon that became known as the "Google Effect," and Risko and Gilbert (2016) generalized such findings into the broader construct of cognitive offloading, the strategic delegation of cognitive work to external devices. This trajectory reframed the issue from pathology toward an adaptive and context-dependent strategy. The premise that offloading is inherently detrimental has itself been questioned: in a meta-analysis published in *Nature Human Behaviour*, Scullin et al. (2025) found that technology use was associated with reduced cognitive decline among older adults—an effect they termed "digital scaffolding." Taken together, these studies indicate that the memory consequences of digital tools are population-dependent and cannot be assumed to be uniformly negative.

A parallel body of work has examined attention. Mark (2023) reported observational evidence of declining durations of sustained focus that coincided with the proliferation of digital media. Klingberg et al. (2025) contributed greater specificity and stronger inferential leverage through a four-year longitudinal study of 8,324 children, in which social media use—but not television or gaming—was associated with increasing symptoms of inattention, implicating the format of the medium rather than screen exposure as such. Firth et al. (2019) advanced a mechanistic interpretation, contending that the interactive and algorithmically curated character of social media imposes distinctive attentional demands. Across this literature, however, much of the available evidence remains correlational, and it is not yet established whether the observed attentional shifts reflect durable change or context-bound adaptation.

A third line of inquiry has sought to ground these behavioral patterns in neural activity. Using electroencephalography, Sharma et al. (2025) associated social media engagement with gamma surges (35–45 Hz) during emotional content, elevated theta activity (4–8 Hz) during social comparison, and alpha suppression. Zhang et al. (2021) identified fragmented reading patterns, reporting increased parieto-occipital alpha and decreased frontal gamma among frequent digital readers. These findings offer convergent neural signatures for the memory- and attention-level effects described above, though, being largely cross-sectional, they speak to association rather than causation.

Considered as a whole, this literature exhibits three notable features. The memory, attention, and neurophysiological strands have advanced largely in parallel and have rarely been integrated; the evidence is methodologically mixed and directionally contested, as the tension between deficit-oriented accounts of offloading and the scaffolding finding of Scullin et al. (2025) illustrates; and no existing account links externalized memory, fragmented attention, and reduced processing depth within a single explanatory structure, while the social-cognitive dimension implied by heavy social-media use remains largely untheorized and untested. The present study addresses this gap by advancing an integrative framework that spans these domains while distinguishing explicitly between its empirically tested and hypothesized components.

The framework integrates four established theories: Baddeley's (2000) Working Memory Model, Posner and Petersen's (1990) Attention Network Theory, cognitive offloading theory (Risko & Gilbert, 2016), and Craik and Lockhart's (1972) Depth of Processing theory. It comprises three empirically tested tiers and one hypothesized extension. The first tier, memory offloading, is grounded in cognitive offloading theory and the Google Effect. The second, attentional fragmentation, derives from attention network theory. The third, the shallow processing loop, follows from Depth of Processing theory, whereby the brief, surface-level encoding characteristic of short-form scrolling yields weaker memory traces than elaborative processing. The fourth, social-cognitive erosion, is offered as a hypothesized extension that the present study does not directly assess. Whereas "digital dementia" functioned as a general alarm, the Google Effect addressed memory alone, and attention-fragmentation research has been confined to a single domain, the proposed framework unifies these phenomena within a single multi-domain account. The first three tiers are testable with the present data, while the fourth is advanced as a candidate for future research employing dedicated measures of social cognition.

3. Methodology

Participants

A total of 180 university students (99 female; M age = 21.7, SD = 2.0; range 18–25) were recruited from three universities in [City/Country] via campus advertisements. Groups: Heavy (≥4 h/day, n = 62), Moderate (1–3 h/day, n = 71), Light (<1 h/day, n = 47), based on device-verified screen time (iOS/Android). This compares usage intensity rather than including a true non-social-media control. Inclusion: age 18–25, university enrollment, ≥6 months smartphone use, normal/corrected vision and hearing. Exclusion: neurological disorders, ADHD, psychotropic medication, sleep disorders, substance use disorders. Unassessed potential confounders: SES, subclinical ADHD traits, physical activity, non-SM device use. Sample size: G*Power 3.1.9.7 (Faul et al., 2009); MANOVA, 3 groups, 5 DVs, $f^2 = 0.0625$, $\alpha = .05$, power = .80 → minimum n = 159.

Measures

Self-report: BSMAS (Andreassen et al., 2016; α = .89), DCOS (10 items; α = .85), CFSA (12 items, 5 subscales; α = .91), DASS-21 (Lovibond & Lovibond, 1995; αs = .87–.91), PSQI (Buysse et al., 1989; α = .82). Shared method variance among self-report measures is acknowledged. Battery: Digit Span (PsyToolkit v3.4.6; Stoet, 2010, 2017), Trail Making A/B (PEBL v2.1; Mueller & Piper, 2014), Stroop, RAVLT, N-back 2-back, CPT, MST (Stark et al., 2019). Counterbalanced. Composite = z-score mean of Digit Span Backward, RAVLT Delayed, N-back Accuracy, CPT Omissions (reversed), MST LDI.

EEG: Emotiv EPOC X, 14-channel, 128 Hz, 10–20 montage (AF3/F7/F3/FC5/T7/P7/O1/O2/P8/T8/FC6/F4/F8/AF4), CMS/DRL reference, impedance <20 kΩ. Preprocessing: MNE-Python v1.6.1 (Gramfort et al., 2013); 0.5–45 Hz bandpass, ICA artifact rejection, ±100 µV threshold. Welch's method for band power. Six conditions: rest EO, rest EC, SM scrolling (10 min), long-form reading (10 min), recovery (5 min), N-back.

Data Analysis

Screen-time distribution was inspected via Shapiro–Wilk and skewness/kurtosis; the variable showed positive skew (1.04) and was log-transformed for regression and indirect-effect analyses. Group-based analyses retained the original h/day metric to preserve interpretability of the Heavy/Moderate/Light thresholds. To assess potential attrition bias, demographic characteristics of excluded volunteers (n = 11) were compared with the retained sample (n = 180) using chi-square and t-tests; no significant differences emerged on age, gender, or year of study (all p > .20). MANCOVA (Pillai's Trace; covariates: age, gender, PSQI, DASS-21). Holm–Bonferroni correction across 17 outcomes. Missing data (<2%): EM imputation. Assumptions: Shapiro–Wilk, Box's M (p = .08), Levene's, VIF < 3.2. Hierarchical regression. PROCESS v4.2 (Hayes, 2022; Model 4; 5,000 bootstraps)—reported as statistical indirect effects, not causal mediation. EEG: mixed ANOVA with Greenhouse–Geisser. Qualitative: Braun & Clarke (2006) thematic analysis, dual coding (κ = .84), saturation at n = 24. Software: SPSS 28, R 4.3.2 (R Core Team, 2023). Platform-specific usage (TikTok, Instagram, YouTube) was recorded but not analyzed as a moderator in the primary analyses; this is acknowledged as a limitation.

4. **Results**

Demographics and Social Media Patterns

Groups were comparable on age and gender (ps > .05) but differed on GPA, sleep, DASS-21, and PSQI (Table 1). Heavy Users averaged 5.9 h/day SM screen time (SD = 1.0) vs. 2.4 (Moderate) and 0.7 (Light), F(2, 177) = 356.8, p < .001. Heavy Users consumed 68.2% short-form content vs. 28.9% for Light. BSMAS: Heavy M = 23.8 vs. Light M = 11.2, F = 141.7, p < .001. DCOS: Heavy M = 37.4 vs. Light M = 22.4, F = 88.3, p < .001.

Table 1. Participant Demographics and Confound Variables by Group

Variable	Heavy (≥4 h/day)	Moderate (1–3 h/day)	Light (<1 h/day)	Total
n	62	71	47	180
Age (years), M (SD)	21.8 (2.1)	21.5 (1.9)	21.9 (2.0)	21.7 (2.0)
Male, n (%)	28 (45.2%)	31 (43.7%)	22 (46.8%)	81 (45.0%)
Female, n (%)	34 (54.8%)	40 (56.3%)	25 (53.2%)	99 (55.0%)
GPA, M (SD)	3.02 (0.41)	3.18 (0.36)	3.34 (0.32)	3.17 (0.39)
Sleep (hrs/night)	5.9 (0.8)	6.6 (0.7)	7.2 (0.6)	6.5 (0.9)
DASS-21 Depression	13.4 (5.2)	10.2 (4.4)	7.4 (3.5)	10.5 (4.9)
DASS-21 Anxiety	12.1 (4.8)	9.5 (4.0)	6.8 (3.1)	9.6 (4.4)
DASS-21 Stress	15.3 (5.9)	11.8 (4.6)	8.9 (3.7)	12.2 (5.3)
PSQI Total Score	8.2 (2.3)	6.7 (2.0)	5.2 (1.8)	6.8 (2.4)

Note. DASS-21 = Depression Anxiety Stress Scale-21; PSQI = Pittsburgh Sleep Quality Index. Groups comparable on age, F(2, 177) = 0.62, p = .54, and gender, χ²(2) = 0.12, p = .94.

Neuropsychological Performance

Multivariate test: Pillai's Trace = .42, F(10, 344) = 8.71, p < .001, η²p = .31. All 17 measures significant after Holm–Bonferroni correction (Table 2). Largest effects: N-back Accuracy (η²p = .41), MST LDI (.37), RAVLT Delayed (.35). Consistent graded pattern (H < M < L or H > M > L). Domain composites: Episodic Memory (.32), Sustained Attention (.30), Processing Speed (.28), Working Memory (.27), Executive Function (.25)—all significant. These patterns are consistent with—but do not establish—a dose–response association.

Table 2. Neuropsychological Test Performance by Social Media Usage Group

Test	Heavy *M (SD)*	Moderate *M (SD)*	Light *M (SD)*	*F*	*p*	*η²p*	Post-hoc

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Digit Span Forward	8.1 (1.3)	8.8 (1.2)	9.5 (1.0)	16.4	<.001	.16	H<M<L
Digit Span Backward	5.4 (1.2)	6.3 (1.0)	7.2 (0.9)	28.8	<.001	.24	H<M<L
Trail Making A (s)	39.8 (7.1)	34.6 (6.0)	29.4 (5.1)	31.2	<.001	.27	H>M>L
Trail Making B (s)	86.5 (14.3)	74.2 (12.5)	63.7 (10.6)	36.5	<.001	.31	H>M>L
Stroop Interference	28.2 (5.4)	33.5 (4.8)	38.4 (4.2)	25.7	<.001	.22	H<M<L
RAVLT Trial 1	6.2 (1.5)	7.4 (1.3)	8.5 (1.2)	22.1	<.001	.20	H<M<L
RAVLT Trial 5	10.3 (1.8)	11.8 (1.5)	13.1 (1.2)	34.2	<.001	.29	H<M<L
RAVLT Delayed Recall	7.2 (2.0)	9.1 (1.8)	11.2 (1.5)	42.1	<.001	.35	H<M<L
RAVLT Recognition	10.4 (1.8)	11.7 (1.4)	13.0 (1.1)	24.6	<.001	.22	H<M<L
N-back Accuracy (%)	72.4 (6.8)	80.8 (5.9)	88.6 (4.8)	54.8	<.001	.41	H<M<L
N-back RT (ms)	714 (84)	648 (73)	582 (61)	38.6	<.001	.32	H>M>L
CPT Omissions	9.1 (3.0)	6.2 (2.4)	3.8 (1.9)	39.3	<.001	.33	H>M>L
CPT Commissions	11.2 (3.4)	8.7 (2.8)	6.1 (2.0)	28.4	<.001	.24	H>M>L
CPT Hit RT (ms)	522 (61)	471 (52)	423 (46)	31.7	<.001	.27	H>M>L
CPT RT Variability	86.5 (15.1)	71.2 (12.6)	58.7 (10.2)	33.5	<.001	.29	H>M>L
MST LDI	0.31 (.11)	0.44 (.10)	0.58 (.09)	47.6	<.001	.37	H<M<L
MST Recognition	0.67 (.09)	0.74 (.08)	0.82 (.07)	26.8	<.001	.23	H<M<L

Note. MANCOVA controlling for PSQI, DASS-21, age, gender. Holm–Bonferroni corrected. H = Heavy, M = Moderate, L = Light.

Regression and Indirect Effects

Confounds: $R^2 = .24$. Adding SM variables: $R^2 = .43$ ($\Delta R^2 = .19$; SM time $\beta = -.37$). Adding mechanisms: $R^2 = .57$ ($\Delta R^2 = .14$; short-form $\beta = -.33$, DCOS $\beta = -.29$; Table 3). The $R^2 = .57$ should be interpreted cautiously given predictor overlap and shared method variance. The statistical indirect effect through cognitive offloading (Table 4; B = -0.26, 95% CI [-0.36, -0.17]) is consistent with but does not confirm causal mediation.

Table 3. Hierarchical Multiple Regression Predicting Composite Cognitive Performance

Predictor	***B***	***SE***	***β***	***t***	***p***	***R²***	***ΔR²***
Step 1: Confounds						.24	.24
Age	-0.04	.02	-.11	-2.01	.046		
Gender	0.07	.05	.08	1.42	.158		
PSQI Total	-0.21	.04	-.31	-5.42	<.001		
DASS-21 Total	-0.18	.03	-.28	-4.87	<.001		
Step 2: + SM Usage						.43	.19
SM screen time	-0.29	.05	-.37	-6.12	<.001		
BSMAS Total	-0.18	.04	-.24	-4.33	<.001		
Step 3: + Mechanisms						.57	.14
DCOS	-0.22	.04	-.29	-5.41	<.001		
Short-form (%)	-0.31	.06	-.33	-5.76	<.001		

Note. Composite = z-score mean of Digit Span Backward, RAVLT Delayed, N-back Accuracy, CPT Omissions (reversed), MST LDI. All VIFs < 3.2.

Table 4. Statistical Indirect Effect: SM Time → Cognitive Offloading → Episodic Memory

					95% Boot. CI	
Path	***B***	***SE***	***t***	***p***	***LL***	***UL***

Path a: SM Time → Cog. Offloading	0.61	.07	8.71	<.001	.47	.75
Path b: Cog. Offloading → Memory	-0.42	.06	-6.88	<.001	-.54	-.30
Total effect (c)	-0.53	.08	-6.62	<.001	-.69	-.37
Direct effect (c')	-0.27	.07	-3.84	<.001	-.41	-.13
Indirect effect (a × b)	-0.26	.05	—	—	-.36	-.17

Note. PROCESS v4.2 Model 4, 5,000 bias-corrected bootstrap samples. Covariates: age, gender, PSQI, DASS-21. The indirect effect is statistically significant (95% CI excludes zero) but does not confirm causal mediation in this cross-sectional design.

EEG Findings

During SM scrolling, Heavy Users showed elevated theta (M = 11.8 vs. Light 8.1 μV²/Hz; $\eta^2p = .25$), suppressed alpha (9.1 vs. 12.7; $\eta^2p = .21$), elevated gamma (7.9 vs. 5.9; $\eta^2p = .13$). During N-back: elevated beta (18.7 vs. 15.1; $\eta^2p = .16$). These should be interpreted cautiously given the consumer-grade EEG system and multiple comparisons.

Qualitative Findings

Eight themes from interviews (n = 30): attentional fragmentation (25/30), short-form habituation (24/30), cognitive overload (23/30), digital memory dependency (21/30), deep reading decline (20/30), sleep disruption (19/30), emotional dysregulation (18/30), failed detox (16/30). Themes converge with quantitative patterns, though demand characteristics may have primed digital-related responses.

5. Discussion

This study found that heavier social media use was associated with lower neuropsychological performance across multiple domains in university students. The converging quantitative, neurophysiological, and qualitative findings extend prior correlational work by integrating multiple modalities within a single design.

Structural Parallels and Critical Distinctions

The largest effects involved hippocampal pattern separation (MST LDI, $\eta^2p = .37$), episodic consolidation (RAVLT Delayed, .35), and working memory updating (N-back, .41)—functions that deteriorate earliest in Alzheimer's. These parallels are descriptive, not pathological. Alzheimer's involves irreversible neurodegeneration; the present patterns likely reflect neuroplastic adaptation—potentially reversible. The label is a heuristic for multi-domain associations, not a clinical claim.

Evaluating the Four-Tier Model

Tier 1 (Memory Offloading): supported by the indirect effect analysis (~49% of SM–memory association) and DCOS predicting performance independently (β = -.29). However, directionality is undetermined. Tier 2 (Attentional Fragmentation): supported by CPT effects ($\eta^2p = .24$–$.33$), alpha suppression persisting into recovery, and 83% interview endorsement. Tier 3 (Shallow Processing): supported by short-form content's predictive strength (β = -.33) and theta elevation during scrolling, consistent with Craik and Lockhart's (1972) prediction that shallow encoding produces weaker memory traces. Tier 4 (Social-Cognitive Erosion) is presented as a hypothesized extension rather than an empirically supported tier: only indirect support via a single CFSA subscale is available, and dedicated social-cognition assessment (e.g., theory-of-mind tasks, emotion recognition batteries) is required before this tier can be claimed. We retain it in the framework to flag a candidate domain for future research, not as an established finding.

EEG Findings in Relation to Satani et al. (2025)

The present EEG findings of elevated theta and suppressed alpha during scrolling in heavy users are directionally consistent with Satani et al. (2025), who reported similar alpha suppression and increased beta/gamma activity in a 24-channel laboratory EEG paradigm during a 30-min continuous social media session. Two design differences temper direct comparison. First, Satani et al. measured EEG continuously during social media use, allowing analysis of time-course and post-engagement recovery dynamics; the present study compared discrete experimental conditions (scrolling, reading, recovery) across groups, which is informative for between-group differences but less sensitive to within-session dynamics. Second, the present consumer-grade 14-channel system has lower spatial resolution than the 24-channel laboratory setup. The convergence across these distinct paradigms strengthens confidence in the alpha-suppression pattern as a robust correlate of heavy social media engagement, though replication with research-grade EEG and continuous paradigms is needed before mechanistic claims are warranted.

Usage Behaviors vs. Screen Time

Behavioral mechanisms (offloading, short-form content) explained 14% unique variance beyond screen time. This suggests how people use social media may matter as much as how much, with implications for intervention design. However, predictor overlap and shared self-report variance complicate interpretation.

Limitations

Key limitations include: (1) cross-sectional design precluding causal inference—reverse causation and selection effects are equally plausible; (2) university-student sample limiting generalizability; (3) partial reliance on self-report for content type; (4) uncontrolled confounders (SES, subclinical ADHD, physical activity, substance use); (5) consumer-grade EEG with limited spatial resolution and multiple-comparison concerns; (6) shared method variance among self-report measures; (7) the "Digital Alzheimer's" metaphor risks overpathologizing normal student cognitive variability; (8) platforms were aggregated rather than analyzed separately, although TikTok, Instagram, and YouTube likely differ in cognitive demand—platform-specific moderation should be tested in future work; (9) demand characteristics in the qualitative phase: participants knew the study examined "Digital Alzheimer's," which may have primed them to report cognitive complaints they would not have volunteered in a neutrally framed interview. Furthermore, group differences in GPA, sleep, and distress suggest systematic baseline differences that may reflect both causes and consequences of usage patterns.

Implications and Future Directions

Provisional implications include educational strategies counteracting offloading (retrieval practice, handwritten notes), clinical consideration of digital habits in cognitive assessments, and targeting specific usage behaviors in public health guidance. Future work should prioritize longitudinal designs, RCTs of digital detox, dedicated Tier 4 assessment, expanded populations, and fMRI integration.

6. Conclusion

Heavier social media use was associated with lower cognitive performance across multiple domains in this university sample. The "Digital Alzheimer's" framework is offered as a descriptive-integrative account with three empirically supported tiers (Memory Offloading, Attentional Fragmentation, Shallow Processing Loop) and one hypothesized extension (Social-Cognitive Erosion). The framework is descriptive rather than causal: the cross-sectional design supports associational inferences but not the multi-tier causal architecture the model could be misread to imply. The findings highlight the potential importance of specific usage behaviors beyond screen time quantity. Whether these associations are causal, reversible, or generalizable remains for longitudinal and experimental research to determine.

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