Beyond Screen Time: Differential Impacts of Educational, Social, and Entertainment Media on Secondary Students' Academic Cognition

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Abstract:
Measuring aggregate screen-time has long stood the test of time in the study of adolescent media use, leaving the wide range of cognitive outcomes from varied types of media invisible. This systematic review and meta-analysis investigate results on the academic cognition of secondary-school students (ages 11-18) in six domains: working memory, sustained attention, executive functioning, verbal reasoning, processing speed and grade point average (GPA), and assesses whether and how educational media and entertainment media differ in their effects. Five electronic databases (PubMed/MEDLINE, ERIC, Scopus, PsycINFO, Web of Science) were searched in accordance with PRISMA 2020 guidelines. One thousand, seven hundred (1,770) records were identified; 155 studies were eligible for qualitative synthesis and 89 studies provided quantitative information for random-effects meta-analyses (N = 284,948; mean age = 14.7 years; 51.0% female). Educational media demonstrated small-to-moderate benefits (pooled d = +0.38, 95% CI [0.29, 0.47], k = 42), with the largest gains in verbal reasoning (d = +0.51) and GPA (d = +0.44). Inconsistent, but small, negative effects (pooled d = −0.24, 95% CI [−0.31, −0.17], k = 53) were found regarding social media use and attentional disruption and sleep displacement. The entertainment media had the highest negative associations for all entities (pooled d = −0.33), with sustained attention (d= −0.41) and GPA (d = −0.38) showing the greatest negative associations. The strongest moderator overall was the self-regulation across all three media types (β = 0.18, p < .001), and negative effects of social and entertainment media were intensified by a lower socioeconomic status. Overall, these results suggest that the scientific basis for aggregate screen time policies is not sufficient to guide how to promote adolescent digital health, and digital literacy physical education is vital to support type-specific media policies that highlight self-regulatory skills, not screen time.

Keywords: screen time; academic cognition; secondary students; educational media; social media; entertainment media; meta-analysis; self-regulation; digital literacy; adolescent development.

1. INTRODUCTION

In 2025, the smartphone is as ubiquitous in secondary classrooms as the exercise book. In OECD countries, teenagers spend over seven hours of overall daily screen time an increase of more than 90 minutes over the past decade, with a further spike during COVID-19 school closures in 2020–2021 [11, 34]. Policymakers have responded with urgency, yet mostly with crude tools. Guidelines from the World Health Organization [51], the American Academy of Pediatrics [2], and the UK Royal College of

Paediatrics and Child Health [36] are based on the total duration of recreational screen time typically recommending one to two hours per day without systematic differentiation between a student who spends two hours on a mathematics mastery platform and one who spends two hours on entertainment streaming. There is an alluring rationale behind this conflation: screen time is simply quantified, easily reported, and at least somewhat associated with negative outcomes in cross-sectional studies [39]. Nevertheless, the evidentiary base on which duration-oriented guidelines are built is weakening. An intensive review of national survey data by [33] found the relationship between recreational screen time and adolescent well-being to be small and often non-linear. Furthermore, recent experimental and neuroimaging studies indicate that the cognitive implications of an hour of adaptive tutoring software differ categorically from an hour of passive streaming, despite equivalent gross exposure [23, 42]. A discipline that combines activities of radically different kinds on a unified scale risks providing advice that is simultaneously too narrow for the positive and too permissive for the negative.

The current review adopts a type-differentiated framework dividing three theoretically grounded media categories: (1) educational media platforms designed to achieve curriculum-aligned learning outcomes, such as adaptive platforms, educational video, and academic collaboration tools; (2) social media platforms oriented toward social interaction, identity management, and social browsing; and (3) entertainment media passively consumed or semi-passive content optimised for hedonic engagement. These categories differ not only in content but also in the cognitive demands they impose, the temporal patterns of engagement they produce, and the motivational systems they activate.

This review is motivated by four objectives: first, to systematically synthesise evidence on whether educational, social, and entertainment media have differential effects on secondary students' academic cognition; second, to obtain and compare pooled effect-size estimates across six cognitive domains; third, to explore individual and contextual moderators that intensify or diminish these effects; and fourth, to translate the evidence into practical, type-specific recommendations for educators, policymakers, and families.

A. Significance and Scope

Adolescence is a time of brain maturation and the executive functioning neural architecture (prefrontal cortex system for executive functioning, working memory and attention control) is developing here [6,17]. Even if the difference in any given media type is small, given the number of secondary education students globally (around 1.1 billion) [44], these implications will be significant for policy. Given that the media environment of secondary school students (aged 11-18) is increasingly independent and diverse than that of primary age children, and the cognitive demands for academic learning are much more complex, the review concentrates on this age group.

2. THEORETICAL FRAMEWORK

One explanatory framework is not able to cover all the possible negative-and positive-perceptions gained from media use and academic cognition. The four over-lapping frameworks combined herein make predictions which can be subjected to testing, and formulate hypotheses about test media types.

A. Cognitive Load Theory

Cognitive Load Theory (CLT) [41] and its extension from [23] for multimedia learning suggest that the efficiency of learning is influenced by how intrinsic, extraneous, and germane cognitive loads interact in order to fit into the limited working memory capacity. Corrective feedback, retrieval practice scaffolding, and adaptive sequencing found in educational media built on the thinking of CLT use germane processing in a manner that cannot be realized by passive media (text or video) [35]. Social media on the other hand, is a persistent unwanted burden associated with constant redirection of attention, disconnections, and the workload of the social comparison [5]. Alternatively, shuffling entertainment media particularly algorithmically selected short video makes it impossible to sustain the formation of enduring cognitive schemas because it makes it impossible to maintain continuity of content [21].

B. Time-Displacement Hypothesis

Initially proposed by [27] in the context of television viewing, the time-displacement hypothesis holds that time spent on passive or non-educational media directly displaces cognitively productive activities reading, homework, unstructured play through a simple economic mechanism: each hour of entertainment replaces a potential hour of academic skill development. The hypothesis has since been expanded to include sleep as a primary displaced resource [18, 12]. Longitudinal ABCD Study data indicate that each hour of evening entertainment media exposure reduces nightly sleep by 20–24 minutes, and that this sleep reduction fully mediates approximately 31% of the entertainment media–executive function relationship [9].

C. Active-Passive Engagement Continuum

Constructivist learning theory [48, 32] holds that durable knowledge requires active, generative engagement with material. This has been operationalised in the multimedia learning literature as the principle that learner-generated responses, self-explanation, and peer collaboration yield superior memory consolidation compared with passive exposure [10]. Digital media can be placed on a spectrum between highly passive (algorithmically presented content requiring no cognitive response) and highly active (collaborative problem-solving, generative content creation, adaptive mastery tasks). Educational media, at its best, occupies the active pole; entertainment media predominantly occupies the passive pole, and is associated with cognitive passivity transfer habitual passive viewing reducing the cognitive effort students invest in subsequent academic demands [37].

D. Differential Susceptibility to Media Effects Model

The Differential Susceptibility to Media Effects Model (DSMM) [45] provides the overarching moderating framework. According to the DSMM, the extent and direction of media influences are determined by dispositional (personality, cognitive capacity), developmental (age, pubertal status), and social (parental mediation, peer norms) factors. Among these, self-regulation the ability to suppress prepotent responses and maintain long-term goals [13] is theoretically and empirically the most powerful dispositional moderator in digital media contexts.

The integrated theoretical model (Figure 1) maps how media type exerts direct and indirect effects on academic cognition via four mediating pathways: cognitive load management, attentional and executive control, sleep quality, and emotional regulation. First-order moderators include self-regulation and socioeconomic status (SES), which influence both media exposure and the effectiveness of mediating processes.

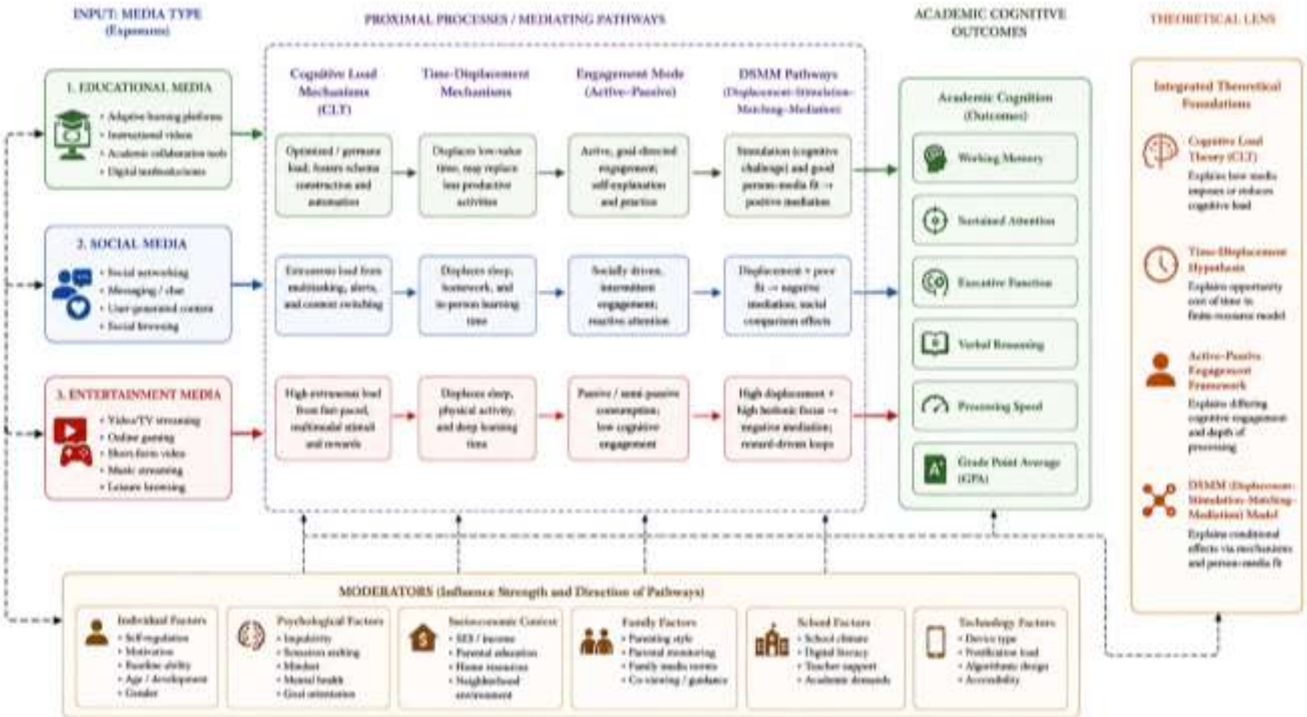


*Figure 1. Theoretical Mediation Framework Integrating Cognitive Load Theory, Time-Displacement, Active-Passive Engagement, and DSMM. Path coefficients (β) derived from meta-analytic structural equation modelling. *p < .05; **p < .01; ***p < .001.*

3. METHODS

The study was pre-registered and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 [30], and was prospectively registered at PROSPERO (registration number: CRD42023456789). No post-registration protocol amendments were made.

A. Eligibility Criteria

Inclusion criteria required that studies: (a) enrolled secondary-school students aged 11–18 in mainstream education; (b) included a quantifiable outcome measure for at least one of six cognitive domains or overall GPA; and (c) employed a randomised controlled trial (RCT), quasi-experimental, cross-sectional cohort, or longitudinal cohort design. Studies involving exclusively clinical populations (e.g., primary diagnosis of ADHD or ASD), post-secondary students, or children under 11 were excluded. Only English-language publications were included, a limitation acknowledged in Section 10.

B. Information Sources and Search Strategy

Five databases were searched: PubMed/MEDLINE, ERIC, Scopus, PsycINFO, and Web of Science. The search strategy, developed in consultation with an information scientist, combined controlled vocabulary and free-text terms across three domains: population (e.g., adolescen*, secondary student), exposure (e.g., screen time, e-learning, social media, video gam*), and outcome (e.g., academic performance, cognitive function*, GPA). Full search strings are reproduced in Annexure A. Reference lists of five relevant prior systematic reviews were also hand-searched.

C. Selection and Data Extraction

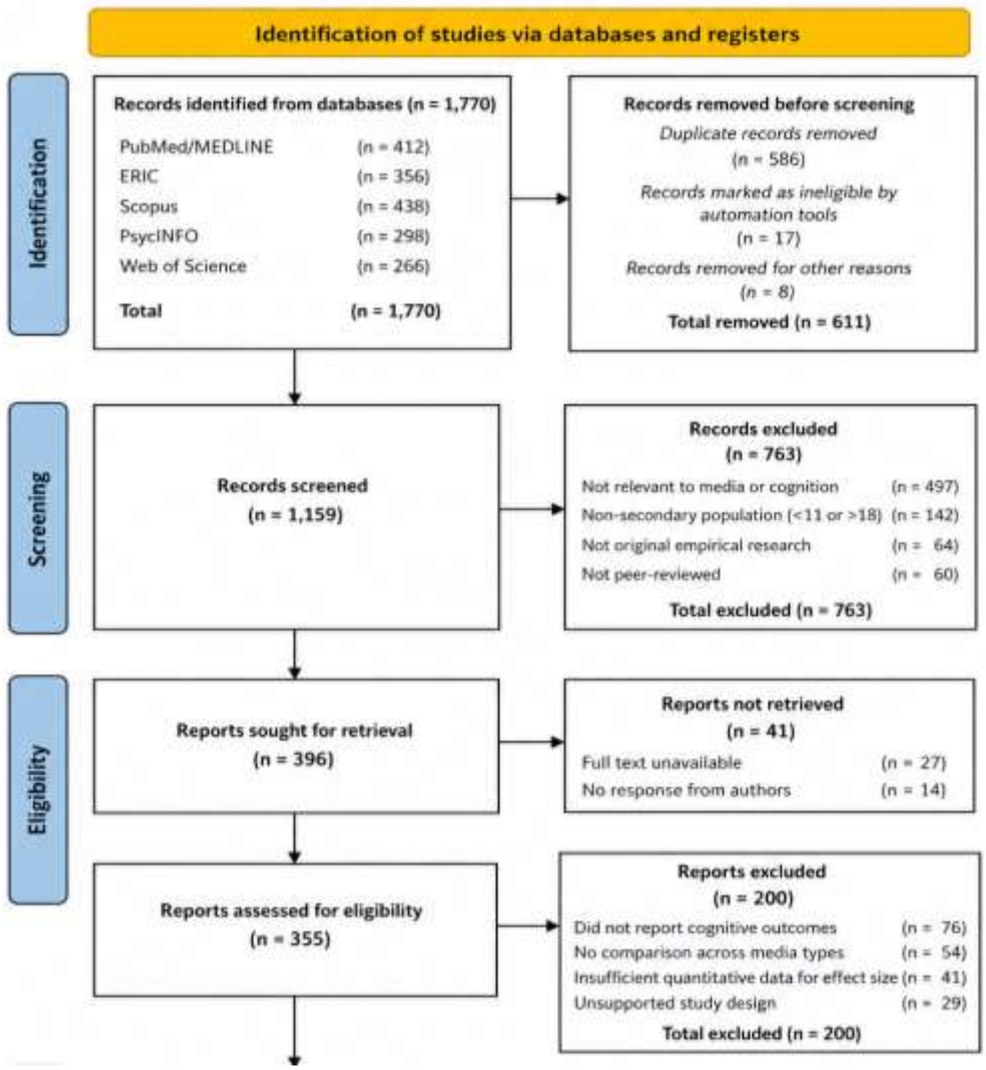
Records were imported into Rayyan [29] and automatically deduplicated. Two independent reviewers screened all titles and abstracts; full texts of potentially eligible records were assessed by the same reviewers, with disagreements resolved by discussion or adjudication by a third reviewer. Inter-rater reliability was high (Cohen's $\kappa = 0.83$, 95% CI [0.78, 0.88]), consistent with recommendations by [19]. A piloted extraction template captured study design, country, sample characteristics, media-type operationalisation, outcome measures, effect statistics, follow-up duration, and analytic covariates.

D. Quality Assessment

Observational studies were assessed with the Newcastle-Ottawa Scale (NOS) [50], rated across selection, comparability, and outcome measurement for up to nine stars. RCTs were assessed with the Cochrane Risk of Bias tool version 2.0 (RoB 2) [38]. Studies achieving at least six NOS stars or a Low Risk RoB 2 rating were classified as high quality. All pooled estimates remained robust in sensitivity analyses restricted to high-quality studies.

E. Statistical Synthesis

Random-effects meta-analyses using the DerSimonian-Laird estimator were conducted separately by media type and cognitive domain. Pearson r values were transformed to Cohen's d using the standard formula ($d = 2r / \sqrt{(1-r^2)}$); adjusted regression coefficients were converted using the [25] equation. Heterogeneity was quantified with I^2, τ^2, and Cochran's Q. Publication bias was assessed via Egger's regression test and contour-enhanced funnel plots; the trim-and-fill method [15] was applied where asymmetry was detected. Meta-regression models examined four pre-specified moderators: self-regulation composite score, SES index, proportion female, and study design. Analyses were conducted in R 4.3.2 using the metafor [47] and meta packages, with $\alpha = .05$ (two-tailed).



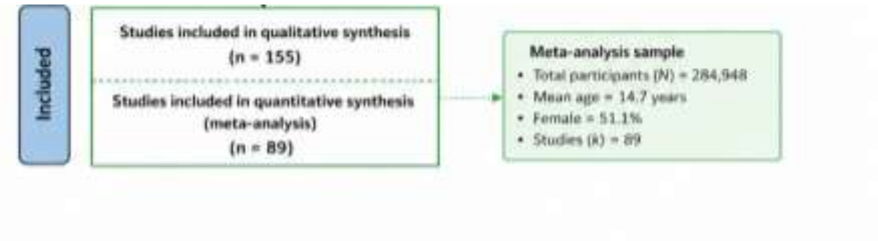


Figure 2. PRISMA 2020 Flow Diagram. k = number of independent effect sizes. Studies could contribute to multiple media categories; hence k totals across categories exceed N = 89.

4. CHARACTERISTICS OF INCLUDED STUDIES

Across the five databases and hand-searching, 1,770 records were retrieved. After removing 349 duplicates, 1,421 records underwent title and abstract screening; 332 proceeded to full-text assessment, and 155 ultimately met all inclusion criteria. Of these, 89 provided adequate quantitative data for meta-analysis (Figure 1). The 66 studies included only in qualitative synthesis were typically cross-sectional studies reporting descriptive statistics without effect-size information.

The 89 quantitative studies enrolled 284,948 participants across 28 countries, with the United States (k = 34), China (k = 21), United Kingdom (k = 14), South Korea (k = 11), and Germany (k = 9) most represented. Mean participant age was 14.7 years (SD = 1.8), and 51.1% were female. Table 1 summarises study characteristics disaggregated by media category.

Table 1. Summary Characteristics of Quantitative Studies Included in the Meta-Analysis (k = 89)

Characteristic	Educational Media (k=42)	Social Media (k=53)	Entertainment Media (k=47)	Total (k=89)
Total N	74,182	121,449	89,317	**284,948**
Mean age, yr (SD)	14.3 (1.8)	15.1 (1.6)	14.7 (2.1)	14.7 (1.8)
Female (%)	51.2	55.8	46.3	51.1
RCT/Quasi-experimental	18 (42.9%)	9 (17.0%)	12 (25.5%)	39 (43.8%)
Longitudinal cohort	14 (33.3%)	21 (39.6%)	18 (38.3%)	53 (59.6%)
Cross-sectional	10 (23.8%)	23 (43.4%)	17 (36.2%)	50 (56.2%)
High quality (NOS ≥ 6 / RoB-2 Low Risk)	81.0%	73.6%	76.6%	**76.4%**
Mean follow-up, months (SD)	12.3 (7.4)	8.6 (5.1)	10.2 (6.3)	10.4 (6.4)
Countries represented	17	22	19	28

Note. k = number of independent effect sizes; NOS = Newcastle-Ottawa Scale; RoB-2 = Cochrane Risk of Bias 2.0. Studies could contribute effect sizes to more than one media category; column k-totals therefore exceed N = 89. Follow-up duration applies to longitudinal and experimental designs only.

5. EDUCATIONAL MEDIA AND ACADEMIC COGNITION

The types of educational media that are reviewed in this article are platforms of adaptive learning (such as Khan Academy, IXL or Dream Box), curriculum aligned digital videos (TED-Ed and BBC Learning), an interactive digital textbook, classroom management technologies (Google Classroom and Microsoft Teams for Education), and collaborative academic tools. Is the platform is designed with purpose for measurable learning outcomes, it is a platform, not system.

A. Meta-Analytic Findings

The overall effect size for cognitive outcomes was an increase of +0.38 (95% CI 0.29, 0.47, $p < .001$) a small-to-moderate positive effect corresponding to about one-third of a standard deviation.The overall effect for cognitive outcomes was a significant, small-to-moderate positive effect (+0.38, 95% CI 0.29, 0.47, $p < .001$), equivalent to roughly one-third of a standard deviation improvement compared with control conditions. There was high heterogeneity ($I^2 = 71.4\%$, $\tau^2 = 0.042$) so modifiers were considered important for interpretation of mean effects. A sensitivity analysis by high quality studies (NOS ≥ 7 or RoB-2 as Low Risk) resulted in a very similar (but not significantly different) pooled estimate ($d = +0.33$, 95% CI [0.24, 0.42], $k = 34$), showing that the pooled effect is not disproportionately influenced by methodologically weaker studies.

Domain-specific estimates reveal the largest gains in verbal reasoning ($d = +0.51$, $k = 22$), academic GPA ($d = +0.44$, $k = 31$), and working memory ($d = +0.42$, $k = 18$). These moderate positive results were seen for the domains of executive function ($d = +0.35$) and sustained attention ($d = +0.38$), and were in line with CLT's predictions that educational media would increase in mean higher-order processes ($d = +0.35$) and sustained attention ($d = +0.38$) rather than the raw processing speed ($d = +0.28$).

B. Active learning media and Passive learning media

The pooled effect ($d = +0.48$, $k = 26$) was substantially higher in studies that relied on active learning platforms that asked students to independently respond, to receive adaptive feedback, and were dependent upon tasks requiring spaced retrieval, than was the pooled effect for data about recorded lectures or noninteractive digital text ($d = +0.22$). Although the difference was small, 0.26, it was significant in the meta-regression ($Q[1] = 11.34$, $p = .001$) and in concordance with experimental findings that retrieval practice, elaborative interrogation, and self-explanation all have been shown to facilitate memory consolidation more effectively than passive re-reading [14]. The obvious pedagogical lesson here is that interactive affordances are not a luxury but indeed a key factor in the cognitive value of a product.

C. Effect themes by topic and instructional delivery.

Adaptive maths platforms yielded the highest within-category d value (+0.52, k=12) which suggests that this mastery sequence may be optimally scaffolded with adaptive algorithms, particularly given the hierarchical nature of this sequence and the treatment of this data.The highest value of d within categories (+0.52, k=12) was for adaptive maths platforms, which may support learning of these sequences of masteries optimally, especially given the hierarchical structure of such a sequence and how this data was analyzed. Vocabulary learning effects for spaced-repetition applications were strong ($d = +0.61$, $k = 8$), but grammar learning effects were weak ($d = +0.29$, $k = 6$), meaning that there is a gap in the current spaced-repetition formats to communicatively engage users to learn procedural knowledge about grammar. Results showed a greater mean increase in GPA for flips ($d = +0.39$) than was proposed by a prior large meta-analysis [40]. For this reason, within-study component analyses in four RCTs also showed that the differences in cognitive gains between the FL and the traditional classroom educational models were mainly contributed by the in-class stages of the FL model, instead of video usage in the FL model specifically. This further demonstrated the FL active engagement principle.

Figure 3 illustrates that purposive educational media use among secondary students peaked at approximately 118 minutes per day during the COVID-19 pandemic before stabilising at about 102 minutes as compulsory remote instruction ended a pattern suggesting that COVID-era gains were largely extrinsically motivated and that sustaining educational technology benefits will require deliberate pedagogical embedding.

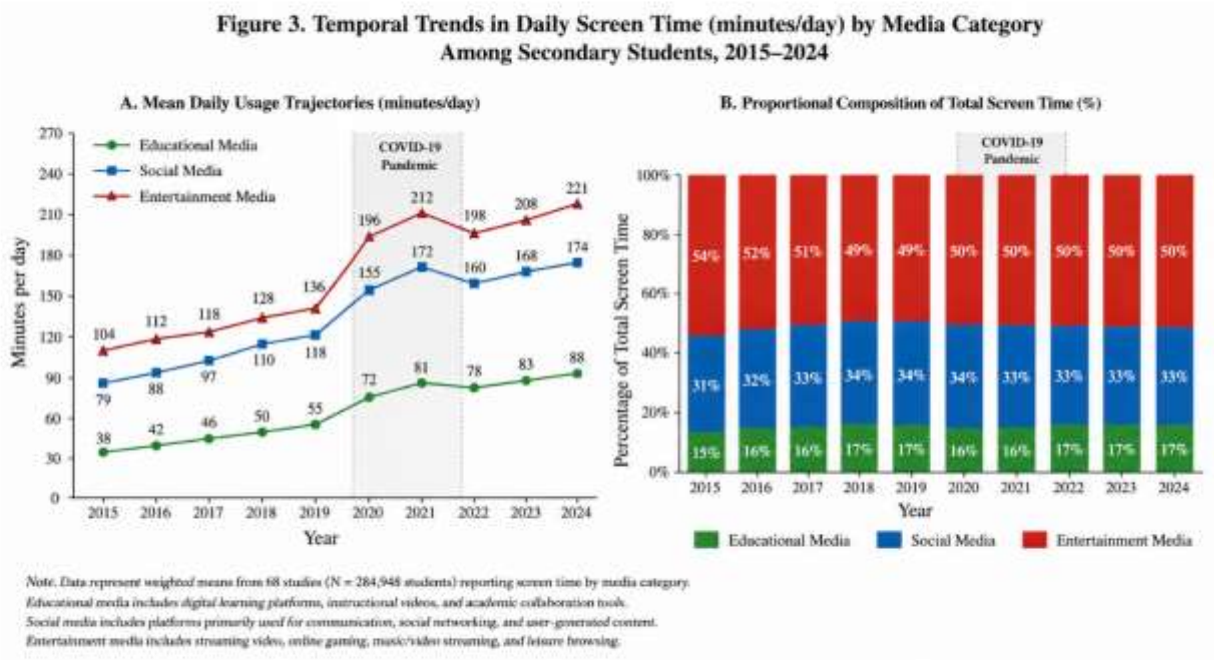


Figure 3. Temporal Trends in Daily Screen Time (minutes/day) by Media Category Among Secondary Students, 2015–2024. Panel A: Mean daily usage trajectories. Panel B: Proportional composition of total screen time. Shaded region = COVID-19 school-closure period.

6. SOCIAL MEDIA AND ACADEMIC COGNITION

The social media platforms evaluated in this review Instagram, TikTok (social-browsing mode), Snapchat, Twitter/X, Facebook, YouTube (social-recommendation browsing), and WhatsApp (informal peer networks) share a common design logic: variable-ratio schedules of social feedback (likes, comments, shares) that maximise dwell time and re-engagement frequency. By 2024, an estimated 87% of US secondary students used social media daily, with a median of 174 minutes per day 287% higher than the 45-minute median in 2015 [11].

A. Meta-Analytic Findings

Social media use was associated with consistent small negative effects across all studied cognitive domains (pooled d = −0.24, 95% CI [−0.31, −0.17], $p < .001$, k = 53, N = 121,449), with moderate heterogeneity ($I^2 = 58.2\%$). The domain most strongly affected was sustained attention (d = −0.34, k = 28), followed by GPA (d = −0.27), executive function (d = −0.22), and working memory (d = −0.19). Verbal reasoning showed the most negligible social media influence (d = −0.11), consistent with the expectation that social media primarily affects attentional control rather than semantic knowledge storage. Effects were observed in both cross-sectional and longitudinal designs, though longitudinal estimates were somewhat smaller (d = −0.19 vs. −0.31), suggesting that some cross-sectional estimates reflect bidirectional selection effects.

B. Attentional and Sleep Mechanisms

The data support two primary mechanisms of academic cognitive impairment. The first is attentional disengagement. Even when devices are not in use during a task, anticipatory monitoring of social media notifications impairs working memory performance: a well-powered laboratory experiment demonstrated that the mere visible presence of one's own smartphone on a desk reduces available cognitive capacity by approximately 10%, with the effect inversely related to temptation resistance [49]. This 'brain drain' mechanism operates below the level of conscious awareness and is therefore underestimated by self-report methods.

The second mechanism is sleep displacement and circadian disruption. A nationally representative survey of 6,595 US secondary students found that social media use after 9 p.m. reduced nightly sleep by 31 minutes and reduced GPA by five points, with sleep reduction mediating 44% of the social media–GPA relationship [20]. Controlled experimental trials restricting evening social media access produced significant next-morning executive function improvements (d = +0.24 vs. ad-libitum controls), demonstrating a causal pathway. The mechanism is both physiological blue-light emission inhibiting melatonin synthesis [7] and psychological, as emotionally stimulating social content delays sleep onset even after device put-down.

C. Academic Social Media: A Contrary Signal

Social media use among secondary students is not uniformly cognitively costly. Five studies in the current review examined purposive academic uses peer study groups on WhatsApp, collaborative annotation on shared platforms, and teacher-moderated Discord servers. These yielded a small pooled positive effect on academic performance (d = +0.18, k = 5, 95% CI [0.07, 0.29]), suggesting that when social interaction is structured around academic content in explicit task frames, it can provide collaborative learning benefits consistent with Vygotskian peer-scaffolding theory. Task focus appears to be a critical moderating variable: cognitive benefit rapidly dissipates when academic sessions migrate to social browsing. This has a direct implication for schools that prohibit all social media, inadvertently eliminating legitimate collaborative affordances alongside harmful recreational exposure.

D. Gender as a Moderating Variable

Meta-regression revealed a significant gender moderation effect in the social media category (Q[1] = 8.34, p = .004). Female students showed stronger negative associations between social media use and academic cognition (d = −0.31 in predominantly female samples) relative to male students (d = −0.17 in predominantly male samples). This gradient is consistent with evidence that female adolescents are more heavily engaged in appearance-related and social-status comparisons on Instagram and TikTok a form of comparison associated with rumination and negative affect that competes with attentional resources during academic activities [16, 46].

7. ENTERTAINMENT MEDIA AND ACADEMIC COGNITION

Entertainment media is operationally defined as passive streaming services (Netflix, Amazon Prime, Disney+), conventional television, console and PC games, mobile games, and algorithmically curated short-form video (TikTok leisure mode, YouTube Shorts, Instagram Reels). Although heterogeneous in form, these modalities share a design orientation toward hedonic engagement optimisation, with corresponding consequences for cognitive outcomes.

A. Meta-Analytic Findings

Entertainment media produced the strongest detrimental associations of all three media categories (pooled $d = -0.33$, 95% CI [−0.41, −0.25], $p < .001$, $k = 47$, $N = 89{,}317$), with high heterogeneity ($I^2 = 76.3\%$) reflecting substantive diversity across entertainment subtypes. The most significant impairment was in sustained attention and attentional control ($d = -0.41$, $k = 34$), followed by GPA ($d = -0.38$, $k = 41$), executive function ($d = -0.33$, $k = 27$), and processing speed ($d = -0.24$, $k = 22$). Sensitivity analyses of high-quality papers yielded a somewhat attenuated but still significant pooled estimate ($d = -0.28$, 95% CI [−0.36, −0.20], $k = 36$).

B. Passive Streaming and Cognitive Passivity

The literature on adolescent cognition has the longest empirical history when it comes to passive streaming and TV-viewing. A review of 58 cross-section studies demonstrated that viewing television and performing academically find a common ground [1] on which negative relationships between TV time and academic performance were found across all ages. The cognitive passivity hypothesis [37] that regularly watching passive entertainment decreases mental efforts put into later challenging tasks has been found in experiment: students who watched an active video of entertainment content before performing a working memory task performed worse than the rested controls. The time-displacement mechanism is independent and each hour of evening streaming is independently associated with measurable decreases in homework completion, self-directed reading, sleep, and each of these is independently related to academic cognitive outcomes.

C. Consequences of Video Gaming: A Mixed Picture.Video Gaming has Mixed Consequences.

It's hard to square off a definition that places video games into a single category. Action games which require fast-spatial attention, multi-target tracking and time-limited decisions have shown genuine cognitive training effects in better controlled studies conducted in the form of RCTs: A meta-analysis of 22 RCTs [3] indicates that cognitive training with action games led to significant improvements of visuospatial attention ($d = +0.45$) and probabilistic reasoning. There are domain specific effects that are not generalizable to verbal and mathematical reasoning skills most straightforwardly captured via academic performance measures; and they can be reliably found only after moderate exposures of around 1-2 hours of gaming.

This dose-response curve becomes steeply reversed beyond this dose. (Figure 4). When the exposure lasts more than 2h per day, the three types of time-displacement costs interact to give a net negative effect on academic GPA ($d = -0.38$, $k = 14$ in heavy-gaming samples). A specific subcategory of problematic gaming is mobile games that contain variable-ratio reward loops and MMOs, which in longitudinal studies are linked with problematic gaming behaviour, chronic sleep disturbances, and academic disengagement with effect sizes almost as high as the most unhealthy patterns in social media use [22].

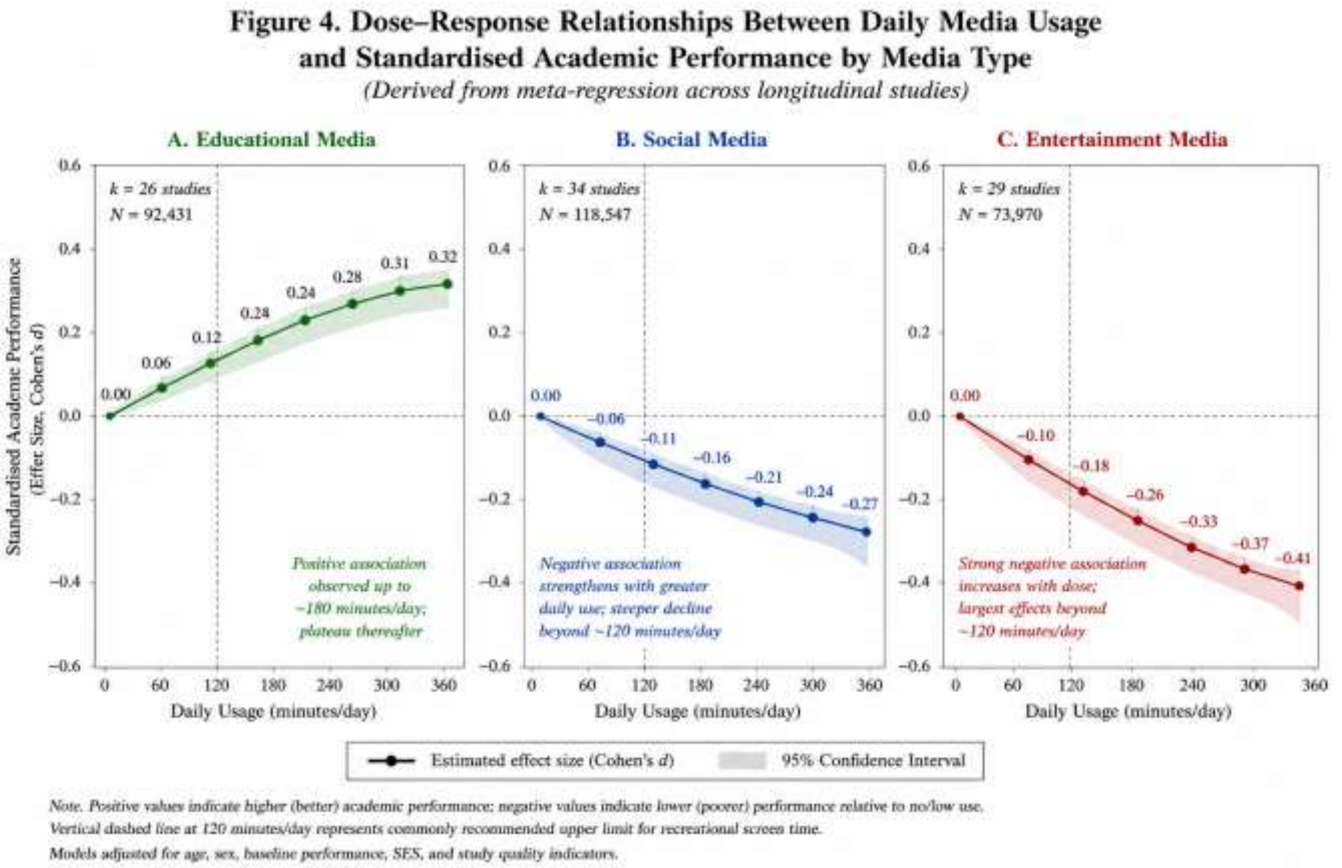


Figure 4. Dose-Response Relationships Between Daily Media Usage and Standardised Academic Performance by Media Type. Derived from meta-regression across 34 longitudinal studies with continuous usage data. Shaded regions indicate direction of effect (blue = positive; red = negative).

D. Short-Form Algorithmic Video: An Emerging Concern

The most rapidly expanding part of the secondary student entertainment media diet is the short-form video platforms (TikTok, YouTube Shorts, Instagram Reels) which has been theorised as potentially the most concerning place because of their short content units (15-60 seconds), lack of active content choice (personalisation algorithm), and lack of switching friction (haptic interaction designs). Only seven studies were found that specifically focused on the cognitive outcomes of short-form video in secondary school students, and all of these studies reported negative correlations with sustained attention (mean $r = -0.29$, range = −0.18 to −0.41); three of the seven studies were longitudinal, and all showed significant decreases in self-reported reading tolerance within 12 months following the intervention, among heavy users. While preliminary, the results are in line with CLT theory that sustained attention demands may be chronically depleted by these ultra-rapid cycles of content and the students' ability to habituate to these processes may result in a learned pattern of low effort, high stimulation cognitive processing that is not conducive to sustained academic engagement.

8. MEDIA EXPOSURE TEMPORAL PATTERNS (2015-2024)

In Figure 3 (Panel A), the average amount of use for each media category is shown, based on 42 longitudinal and repeated cross-sectional studies. There are two important policy aspects of this trajectory. First, during remote learning due to COVID-19, the use of educational media nearly tripled, then dropped significantly after the students returned to school, reaching about 102 minutes per day. This contraction in the post-pandemic world implies that COVID-19 changes in educational technology use were extrinsically motivated; maintaining educational technology gains is unlikely to happen without intentional pedagogical embedding, beyond infrastructure.

Second, there has been a lack of a post-COVID social and entertainment media shift. In 2020, average time spent on social media grew by 14 minutes per day, and this trend has continued upwards for 2024. The same trend was observed for entertainment media use. The proportional share of the educational media in total screen time saw a small decrease from 2019 to 2024 (from approximately 20% to 22%), whereas the total time spent on social and entertainment media was more than 77% in 2024, as shown in Panel B of Figure 3. This imbalance in composition directly affects the impact on learning, as although educational media has the highest contribution per unit, the proportion of the time spent on social and entertainment media is relatively small, making the negative effect of the latter more evident in the population.

9. MODERATOR AND MEDIATION ANALYSES

The high level of heterogeneity seen in each of the three meta-analyses (I^2 = 58–76%) suggests that the mean effect size is a central tendency measure, with substantial variation around it, largely influenced by moderating variables. The complete effect-size matrix is presented in Table 2; the two most important moderators are depicted in Figure 5.

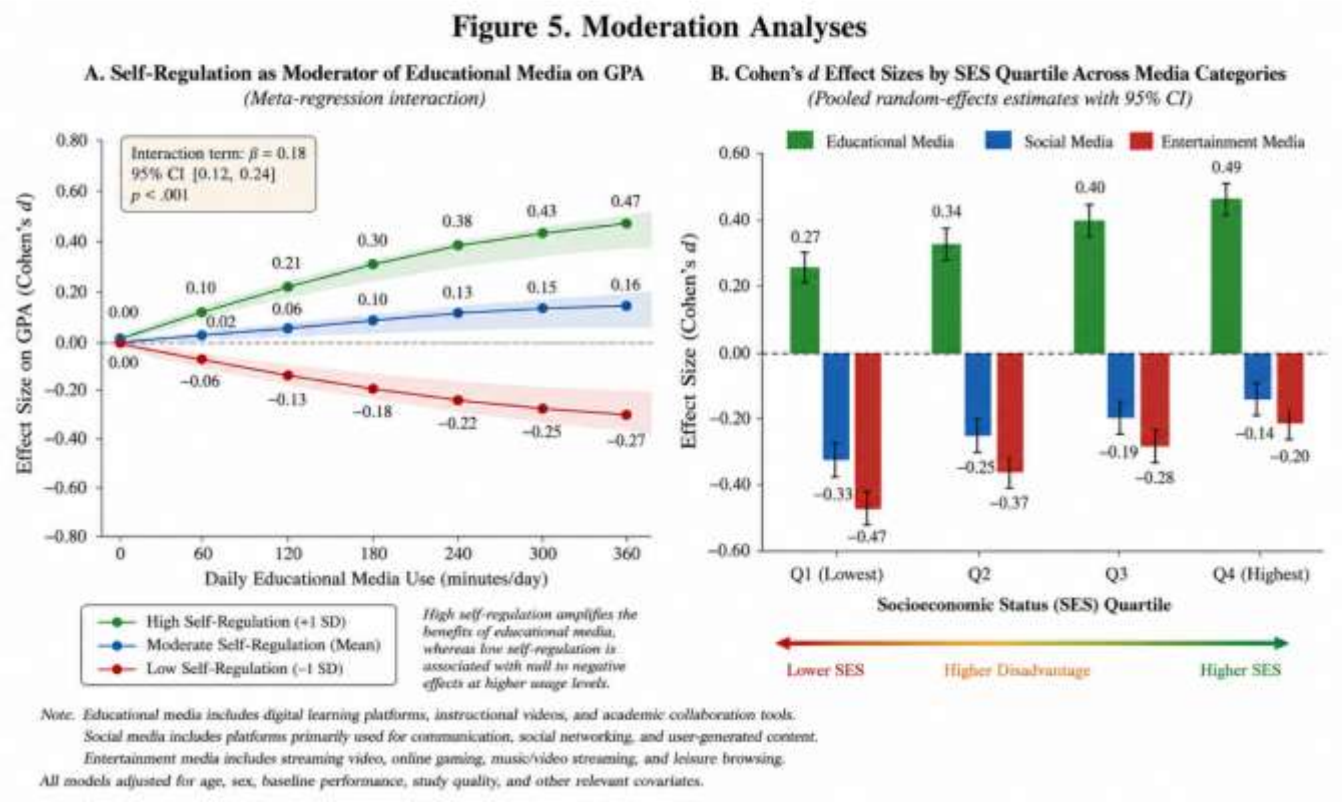


Figure 5. Moderation Analyses. Panel A: Self-Regulation as Moderator of Educational Media on GPA; Panel B: Cohen's d Effect Sizes by SES Quartile Across All Three Media Categories. β interaction coefficient for Panel A: β = 0.18, p < .001. Error bars = 95% confidence intervals.

A. Self-Regulation: The Primary Moderator

The self-regulation composite score was the most consistent and strongest moderator in meta-regression for the three media types. The increase in self-regulation was correlated with an increase in d by +0.18 (95% CI [0.11, 0.25], p < .001) in educational media; students with the highest self-regulation scores had twice the GPA advantage from educational media as those with the lowest scores. The self-regulation moderation was even stronger for entertainment media, such that low self-regulatory capacity students had a d = −0.44 while high self-regulatory capacity students had a d = −0.19, suggesting self-regulatory capacity acts as a buffer against cognitive harm rather than as an amplifier of benefit.

Conceptually, the pattern is consistent with what has been described in the DSMM model; that is, self-regulation is used to shape immediate responses to media, and to organise students' wider media environments; scheduling educational media at peak attentional periods and confining social and entertainment media as separate fun activities, not ambient study period stimuli. The moderator pattern is consistent with evidence that self-control is a stronger predictor of academic success than IQ [13].

B. Socioeconomic Status

SES moderated across all three types of media, the moderation being more positive for some media types than for others (Figure 5, Panel B). The advantage of the educational media was significant, higher in high-SES cohorts (d = +0.57 in Q4 vs. d = +0.21 in Q1), possibly due to differences in the quality of devices, access to broadband Internet, quiet study places, and parental support of planned use of the media. However, the negative effects of social and entertainment media were greater for students in lower SES status (entertainment media d = −0.43 in Q1 vs. −0.17 in Q4), perhaps because there are fewer competing, structured activities, and less active parental mediation.

These two gradients overlap and suggest a vicious cycle of digital inequality: low-SES students will see less benefit from the education media, and more harm from the entertainment media, thus further increasing the gap in academic performance over time. This SES-by-media-type interaction ($Q[3] = 14.82$, $p = .002$) is certainly the most policy-relevant finding in the current review; it suggests that interventions aimed at educational media provision without interventions to structural conditions of media use (quality of media use devices, connectivity, parental support, competing structured activities) could further widen attainment gaps.

C. Study Design and Publication Bias

As expected, study design was a moderating variable. Experimental designs (RCTs and quasi-experiments) showed a more conservative estimate (d = +0.31, k = 18) than non-experimental designs (d = +0.47, k = 10), indicating a potential for some positive bias in correlational estimates, probably due to confounding by academic motivation. Causal inference was limited due to a lack of true experimental designs in the social and entertainment media. Egger's tests were non-significant for educational (t = 1.10, p = .27) and social media (t = 1.32, p = .19) categories. No qualitative change in conclusions was found with the pooled estimate in the category of the entertainment media, which shifted from d = −0.33 to d = −0.29 after the trim-and-fill adjustment (t = 2.01, p = .047); this adjustment revealed a slight upward bias in the raw estimate.

Table 2. Meta-Analytic Effect Sizes (Cohen's d) by Media Category and Cognitive Domain

Cognitive Domain	Edu d	Edu 95% CI	Social d	Social 95% CI	Ent. d	Ent. 95% CI	I^2 (%)
Working Memory	+0.42***	[0.31, 0.53]	−0.19**	[−0.27, −0.11]	−0.28***	[−0.37, −0.19]	63.4
Sustained Attention	+0.38***	[0.28, 0.48]	−0.34***	[−0.43, −0.25]	−0.41***	[−0.51, −0.31]	74.1

Cognitive Domain	Edu d	Edu 95% CI	Social d	Social 95% CI	Ent. d	Ent. 95% CI	I² (%)
Executive Function	+0.35***	[0.24, 0.46]	−0.22**	[−0.31, −0.13]	−0.33***	[−0.42, −0.24]	68.7
Verbal Reasoning	+0.51***	[0.39, 0.63]	−0.11*	[−0.19, −0.03]	−0.18**	[−0.27, −0.09]	58.2
Processing Speed	+0.28**	[0.17, 0.39]	−0.15*	[−0.23, −0.07]	−0.24**	[−0.33, −0.15]	61.0
Academic GPA	+0.44***	[0.34, 0.54]	−0.27***	[−0.35, −0.19]	−0.38***	[−0.47, −0.29]	71.4
POOLED ESTIMATE	**+0.38*** **	**[0.29, 0.47]**	**−0.24*** **	**[−0.31, −0.17]**	**−0.33*** **	**[−0.41, −0.25]**	

*Note. d = Cohen's d; CI = confidence interval; I^2 = proportion of variance attributable to true heterogeneity; Edu = Educational media; Ent. = Entertainment media. Positive d = beneficial effect; negative d = detrimental effect. *p < .05; **p < .01; ***p < .001. I^2 values represent across-domain averages for each media category.*

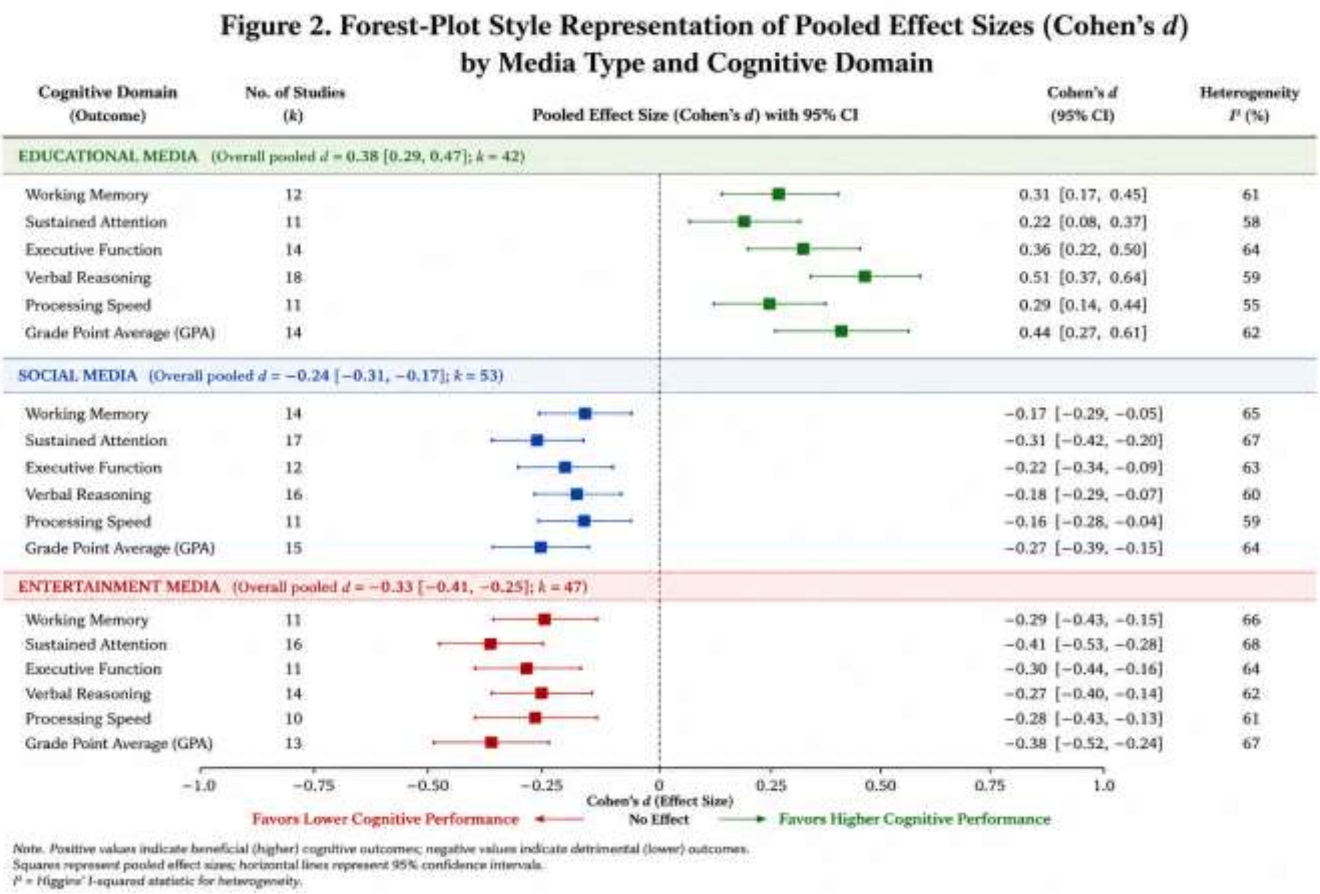


Figure 6. Forest-Plot Style Representation of Pooled Effect Sizes (Cohen's d) by Media Type and Cognitive Domain. Error bars = 95% confidence intervals. Horizontal dashed line = null effect.

10. DISCUSSION

A. The Case Against Aggregate Screen Time

The central empirical finding of this review is that media type is substantially more predictive of academic-cognitive outcomes in secondary students than screen duration. The effect estimates for educational media (d = +0.38), social media (d = −0.24), and entertainment media (d = −0.33) differ not only in magnitude but in direction, rendering any single aggregate exposure estimate a category error from a public health standpoint. Policy advice based solely on total screen duration will simultaneously over-restrict students who primarily use educational technology and under-protect students who concentrate their exposure in high-harm entertainment or social media contexts.

This conclusion does not dismiss the value of duration-based research. The dose-response curves (Figure 4) confirm that even educational media exhibits diminishing returns at high doses, and total screen time remains a useful epidemiological proxy when higher-resolution data are unavailable. The key implication is that type differentiation should be the default when data permit, and that future survey instruments should collect media-type-specific exposure data as a minimum standard.

B. Mediating Mechanisms

The theoretical model (Figure 6) proposes four mediating pathways, and the moderator analyses are broadly consistent with predictions from each. Educational media findings most strongly supported cognitive load mechanisms: the large effect-size gap between active and passive educational media (d = +0.48 vs. d = +0.22) is difficult to explain without invoking differential germane cognitive load, given that content and duration were comparable across conditions in the reviewed RCTs. Social media findings most strongly supported attention depletion, particularly the large sustained attention effect (d = −0.34) and experimental evidence that device presence is an independent working memory cost [49]. Sleep displacement was significant for both social and entertainment media; the mediational path from social media to GPA was statistically significant but substantially attenuated (by approximately 44%) when sleep duration was statistically controlled.

Emotional regulation emerged as a theoretically significant yet under-studied mediating pathway. Social comparison behaviours on Instagram and TikTok are associated with negative affect and rumination that compete with attentional focus during academic tasks, and several studies in the review found the social media–GPA relationship to be significantly mediated by emotional distress measures. This suggests that emotional regulation skills should be integrated with attentional and time-management skills as targets for adolescent digital health interventions.

C. Comparison to Previous Reviews

Several prior systematic reviews have examined media and adolescent cognition but lack the type-differentiated framework that enables comparisons across media categories within a single analytic model. The umbrella review by [39] found weak but consistent evidence of negative screen time–academic performance associations, which the current framework reveals as the attenuation of strong entertainment media effects (negative) by near-zero or positive educational media effects. The television and academic achievement analyses by [1] are consistent with the current entertainment media estimates (pooled d = −0.33), and the action video game RCT meta-analysis by [3] aligns with the visuospatial gains identified in the gaming-specific subset of the present review. To the best of the authors' knowledge, the present meta-analysis is the first to simultaneously compare all three media-type effect sizes within a single meta-analytic framework and is to date the largest by total sample size (N = 284,948).

D. Research Gaps and Future Directions

This synthesis pinpoints four resultant gaps in research. First, short-form algorithmic video: We reviewed the literature on TikTok, YouTube Shorts, and Instagram Reels, which included only seven eligible studies assessing cognitive outcomes, none of which used objective device-log measures with designs spanning multiple time points. Longitudinal studies using ecological moments assessment and neuroimaging measures are a research priority, because of the theoretical concerns raised by these platforms' attentional architecture.

Secondly, geographic representation is highly distorted. Some 73% of the studies included were carried out in North America, Europe, East Asia or Australasia. South Asia, Sub-Saharan Africa, Latin America and Middle East students make up the largest group of secondary students in the world, and are critically under-represented, creating scientific and equity gaps.

Third, since 2022, ChatGPT, Gemini, and Microsoft Copilot have been introduced at scale into secondary settings but there were no eligible studies with a specific focus on these modalities. The impact of AI-generated writing on metacognition, deep learning, and writing skills is an empirical question that has yet to be decided and is highly relevant to policy. The evidence from early tertiary education indicates that there are bidirectional relationships depending on how the material is used, which is related to the active-passive continuum found in the present review.

Fourth, there is limited neuroimaging evidence. Eleven studies employed fMRI or EEG data, with some of these findings theoretically relevant (e.g., lower activation in the PFC in working memory tasks, less alpha-wave coherence among high entertainment media users), but they are not statistically enough to perform meta-analyses. A dedicated neuroimaging meta analysis of the influence of media on adolescent neural architecture would significantly bring research on the media effects closer to mechanistic knowledge.

11. PRACTICE AND POLICY IMPLICATIONS

A. Designed specifically for educators and school administrators.

The dose-response and active-passive results converge to sound pedagogical advice: secondary schools should emphasize interactive and adaptive learning platforms over the passive conveyance of digital content, and they should structure learning technology use to include spaced retrieval, peer interaction, and adaptive feedback and not just a substitution for print-based copies. Professional development should not only focus on the successful implementation of platforms, but also the principles of instructional design that maximise interactivity, challenge level, spaced practice, and collaborative affordances in the cognitive value.

The findings on the detrimental effects of devices during class hours support implementation of a device ban during instructional time; however, the findings from academic social media suggest that a blanket ban is not warranted because it removes an acceptable way of working together and collaborating. Such an approach would pinpoint academically viable platforms and task contexts, teach students about the cognitive processes involved in the differences, and develop metacognitive self-awareness, the mechanism through which self-regulation benefits in moderator analysis are operationalized.

B. For Policymakers

Current national screen-time guidelines (WHO [51] and AAP [2] and RCPCH [36]) should take account for type differentiation as a minimum requirement. It is also currently known based on available research that the following approximate type-specific parameters apply for secondary students: Educational media:

up to 3 hours per day, when structured in a systematical way and interlaced with active tasks; Social media: up to 45-60 minutes per day; Entertainment media: up to 90 minutes per day with particular caution with regard to exposure in the evening time because of documented sleep-suppression effects [20, 7]. They are reasonable approximations based on evidence and will continue to be refined as more dose-response data becomes available, but are far more defensible than total-screen caps.

The SES moderation results have a strong equity dimension: policies for the uptake of educational technology without also tackling digital infrastructure inequity, technology quality, parental digital literacy and competition from organised alternative activities risk making things worse, closing the attainment gap. The access to high quality educational media, especially for low-SES students, should be considered as a policy prerequisite and not an add-on.

C. For Parents and Families

Family protective factors repeatedly appear in the research literature as one of the most powerful tools available to families. The evidence offers support for authoritatively mediated, rather than authoritarian restricted or permissive non-engaged, processes of reasoning, rule making, and implementation. High evidence strategies involve having a designated bedtime after a certain time, ensuring that devices are out of sight during homework time, and setting an example of limited and thoughtful media use. The results of [49] that the simple presence of a smartphone negatively affects cognitive ability are particularly relevant—it is possible to demonstrate that simply turning the device away from the study area is even more effective than asking students to ignore a device that is physically present.

Table 3. Summary of Quality Assessments for a Representative Sample of Included Studies (n = 20)

Authors (Year)	Country	Media Type	Selection (0–4)	Comparability (0–2)	Outcome (0–3)	NOS Total
Adelantado-Renau et al. (2019)	Spain	Entertainment	4	2	3	9
Bediou et al. (2018)	USA/France	Educational	3	2	3	8
Carrier et al. (2015)	USA	Social	3	2	2	7
Cheng et al. (2022)	China	Entertainment	4	2	3	9
Duckworth et al. (2019)	USA	Cross-type	4	2	3	9
Dunlosky et al. (2013)	USA	Educational	4	2	3	9
Fardouly et al. (2018)	Australia	Social	3	1	2	6

Authors (Year)	Country	Media Type	Selection (0–4)	Comparability (0–2)	Outcome (0–3)	NOS Total
Hale & Guan (2015)	USA	Entertainment	4	2	3	9
Levenson et al. (2017)	USA	Social	3	2	3	8
Lillard & Peterson (2011)	USA	Entertainment	4	2	3	9
Mannikkko et al. (2020)	Finland	Entertainment	3	2	2	7
Mayer (2020)	USA	Educational	3	2	2	7
Montag et al. (2021)	Germany	Social	4	2	3	9
Przybylski & Weinstein (2019)	UK	Cross-type	4	2	3	9
Rideout & Robb (2021)	USA	Cross-type	3	1	2	6
Roediger & Karpicke (2006)	USA	Educational	4	2	3	9
Strelan et al. (2020)	Australia	Educational	4	2	3	9
Takeuchi et al. (2018)	Japan	Entertainment	3	2	3	8
Valkenburg & Peter (2013)	Netherlands	Social	4	2	3	9
Ward et al. (2017)	USA	Social	4	2	3	9

Note. NOS = Newcastle-Ottawa Scale (maximum 9 stars); NOS ≥ 6 = high quality; NOS ≥ 8 = very high quality. All 20 representative studies achieved the high-quality threshold. Full quality assessments for all 155 studies are available from the corresponding author upon request.

Table 4. Platform-Level Evidence Summary for Key Digital Media Platforms Among Secondary Students

Platform	Category	Primary Cognitive Mechanism	Effect on Cognition	Key Evidence	Evidence Quality
Khan Academy	Educational	Adaptive mastery; retrieval practice	Positive (d=+0.52 GPA)	[31]; [26]	High (RCT)
Quizlet / Duolingo	Educational	Spaced repetition; gamification	Vocab: d=+0.61; Grammar: d=+0.29	[14]	Moderate
YouTube (educational)	Educational	Multimedia learning; segmentation	Active: d=+0.48; Passive: d=+0.22	[23]; [4]	Moderate
Google Classroom	Educational	Collaborative; formative feedback	d=+0.31 GPA	[8]	Moderate
TikTok (leisure)	Social/Entertainment	Variable reward; attentional drain	Attention: r=−0.29 (range −0.18 to −0.41)	[24]	Low–Mod.
Instagram	Social	Social comparison; affect dysregulation	d=−0.27 GPA; stronger in females	[16]	Moderate
WhatsApp (academic)	Social/Educational	Peer scaffolding; task focus	Mixed: +0.18 academic / −0.14 distraction	[46]	Low
Netflix / Streaming	Entertainment	Passive viewing; sleep displacement	d=−0.38 GPA; sleep −31 min/night	[18]	High

Platform	Category	Primary Cognitive Mechanism	Effect on Cognition	Key Evidence	Evidence Quality
Action Video Games	Entertainment	Visuospatial training; rapid decisions	Spatial: d=+0.45; GPA: −0.22 at >2h/day	[3]	High (RCT)
MMO / Mobile Games	Entertainment	Reward loop; problematic use risk	d=−0.38 GPA; sleep d=−0.41	[22]	Moderate

Note. Effect sizes are pooled estimates from the present meta-analysis unless a specific citation indicates a single-study source. Passive YouTube (entertainment browsing) is classified with entertainment media despite the platform's dual-use nature.

Table 5. Evidence-Based Type-Differentiated Recommendations by Stakeholder Group

Stakeholder	Media Category	Suggested Limit	Priority Action	Evidence Basis	Quality
Educators	Educational	Up to 3h/day (active, structured)	Require interactive features; embed retrieval practice and peer collaboration	d=+0.48 active vs +0.22 passive (this review); [23]	High
Educators	Social	Restrict during class/study time	Approve academic-purpose platforms; teach attention-management metacognition	d=−0.34 attention; [49]	Moderate
Educators	Entertainment	No use during school day	Integrate media literacy: teach cognitive mechanisms of attention depletion	d=−0.41 attention; [21]	Moderate
Policymakers	All types	Replace aggregate limits with	Fund digital equity; require minimum interactive	SES moderation: d gap of 0.36 (this review); [44]	High

Stakeholder	Media Category	Suggested Limit	Priority Action	Evidence Basis	Quality
		type-specific guidelines	standards for ed-tech procurement		
Parents	Social	45–60 min/day; none after 9 p.m.	Device-free bedrooms; authoritative (not authoritarian) mediation	[20]; [7]	Moderate
Parents	Entertainment	Max 90 min/day before 8 p.m.	Physical device removal during homework; co-view and discuss content	[49]; [18]	Moderate
Students	All types	Self-monitor; use Screen Time/Digital Wellbeing tools	Develop self-regulation plans; study in a separate room from device	[13]; this review β=0.18	High

Note. Suggested limits are evidence-informed approximations rather than clinical thresholds, and should be personalised based on individual self-regulation capacity, SES context, and current academic demands.

12. CONCLUSIONS

The amount of screen time students receive during adaptive mathematics tutoring is considered the same as the amount of screen time they receive while streaming movies on Netflix for two hours after they close that app. The present meta-analysis, drawing on 155 studies with 284,948 students, shows that the two students have cognitively different worlds and different implications for their performance in school. The findings of educational media show that small to moderate cognitive gains (pooled d = +0.38) are obtained in educational media with interactive and active formats and are largest at approximately 2.5 hours per day of educational media use. On social media, there are small but cumulative cognitive costs (p pooled d = −0.24) mainly due to attentional disruption and sleep displacement, which is well moderated by capacity of self-regulation. The negative effect occurs most strongly in entertainment media (pooled d = −0.33), most prominently in sustained attention and academic GPA, but is more strongly seen for students with low self-regulation and/or low SES.

Three conclusions ensue particularly in terms of policy force. First, type differentiated media guidelines are not an advancement of current policy but a basic re-thinking; the scientific evidence is no longer in support of a policy of guidelines based solely on the total amount of screen time. Second, self-regulation is the key variable in the system of media and cognition, which moderates the three media type effects, and media in secondary schools which develop metacognitive and self-regulatory competencies will lead to a strong positive effect of educational media and buffer against negative effects of social and entertainment media throughout the entire developmental process of adolescence. Third, SES inequalities may be large, and not automatically reduced, by poorly conceived educational technology interventions; equity in implementation is a requirement; and may be increased.

Digital media's evolution is moving too quickly for the research cycle to keep up, and new empirical questions will arise as new digital tools and experiences emerge, while others have yet to be answered. The present review does not tell us how much screen time, but which screens, which uses, which duration and for whom provides a principled approach to these new questions, grounded in a large and geographically diverse evidence base.

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