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Social Media Use and Adolescent Mental Health: A Meta-Meta-Analysis Followed by a Quantitative Synthesis of Longitudinal Evidence

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Abstract

Social media use has been widely debated as a contributor to adolescent mental health problems, yet evidence regarding the strength and interpretation of this association remains contested. We conducted a meta-meta-analysis of quantitative reviews, followed by a complementary meta-analysis of longitudinal evidence extracted from the included reviews to evaluate associations between social media use and mental health outcomes among adolescents aged 10–19 years. Searches combined nine databases alongside backward and forward citation tracking, last updated in March 2026. Seven eligible meta-analyses were identified from 8,780 records, comprising 11 review-level effect sizes spanning depression, anxiety, and broader internalising symptoms. Social media use was associated with poorer mental health outcomes (*SMD* = 0.21, 95% *CI* [0.16, 0.27], $p < .001$), although heterogeneity was substantial. Despite high quality scores (Mean = 9.57 out of a possible 11), only 3 out of 7 meta-analyses were pre-registered, highlighting the lack of research transparency. To examine the temporal interpretation of the evidence represented within the included reviews, we additionally synthesised 33 longitudinal studies (N_{ES} = 96) identified within the seven included reviews. A three-level random-effects model of these 96 effect sizes yielded a Cohen's d of 0.24 (95% *CI* [0.13, 0.36], $p < .001$). In terms of forward direction, greater social media use was prospectively associated with poorer subsequent mental health (*d* = 0.25, 95% *CI* [0.12, 0.37], $p < .001$), whereas poorer mental health was also prospectively associated with greater later social media use (*d* = 0.18, 95% *CI* [0.10, 0.27], $p < .001$). It is worth noting that both directions are statistically significant, although reverse-direction estimates were smaller in magnitude. Moderator analyses reported by the included meta-analyses were inconsistent, whereas our longitudinal meta-regression found no evidence that mean age or gender composition systematically moderated associations. Overall, findings support a small but consistent association between adolescent social media use and poorer mental health, although longitudinal evidence suggests a more complex and heterogeneous relationship than simple one-way accounts would imply. Future meta-analyses should strengthen conceptual clarity and improve methodological transparency.
Keywords: Social media; Mental health; Adolescents; Meta-meta-analysis; Longitudinal; Meta-analysis

Introduction

Since the early 2000s, the rise of various social networking sites[1] have rapidly gained billions[2] of users in the past two decades. With up to 90% of teenagers claiming to have used social media[3], these platforms have changed the social ecology of adolescence. Youth's heavy engagement with social media has redefined their daily socialization, identity work, information as well as emotional seeking within and beyond school and family contexts. Together with the drastic increase in young social media users, children and adolescents' worsening mental health status[4] is a pressing and concerning social and policy issue. Are these two phenomena happening together merely as a coincidence or are they connected?

Public Concerns on Adolescents' Social Media and Mental Health

In public discourse, current policy directions reflect a strong negative viewpoint against adolescents' social media use. Across the world, governments and schools are increasingly restricting adolescents' access to smartphones and social media. For instance, Australia and the UK announced under-16-year-old social media bans[5,6], while Utah in the US has enacted legislation requiring social media platforms to obtain parental consent before allowing minors under 18 to use their services[7]. These global policy responses have emerged amid growing concerns about social media's role in escalating adolescents' depression[8] and anxiety[9]. Meanwhile, news creatively associates social media with negative terms, such as "doomscrolling[10]" and "brain rot[11]". Such media exposure fuels the existing panic among parents and policymakers to take actions in the direction of a complete ban.

Past Research Evidence: Systematic Reviews and Meta-analyses

Given the heated-up public debate, in the past few years, several systematic reviews and meta-analyses have examined the association between social media use and mental health outcomes. Although many reviews report statistically significant associations between greater social media use and poorer mental health outcomes, conclusions differ regarding the magnitude and practical significance of these effects, with some scholars arguing that average associations are too small to support broad claims of harm[12,13].

Interpretation of these meta-analyses is further complicated by methodological heterogeneity across reviews. Existing meta-analyses differ in their operationalization of social media use, inclusion criteria, and mental health outcomes examined. While some focus specifically on depressive symptoms or anxiety, others synthesize broader constructs such as internalising symptoms, psychological distress, or ill-being[14,15]. Moreover, the evidence base remains dominated by cross-sectional studies, while longitudinal research reports mixed findings that include small average associations alongside substantial between-person variability[16,17].

More recently, Teague et al.[18] synthesised a large body of longitudinal evidence on digital media use and child health and development, similarly reporting small associations between social media use and subsequent mental health outcomes.

Past Research Evidence: Umbrella Reviews

On a higher level, two existing umbrella reviews examined this topic[19,20]. However, these reviews primarily summarized findings narratively and therefore could not quantitatively determine the overall magnitude and consistency of associations across existing meta-analyses. Nor did they formally assess the extent to which overlapping primary studies may have inflated apparent convergence across reviews. More recently, Tølbøll et al.[21] synthesised 72 reviews, including 20 meta-analyses, and examined whether differences in statistical power may contribute to inconsistent findings across reviews. However, existing umbrella reviews have not statistically synthesised effect estimates across meta-analyses while formally quantifying the extent of primary-study overlap between them. Consequently, it remains unclear whether divergent conclusions within the literature reflect genuinely inconsistent quantitative estimates, differences in the underlying evidence base, or different interpretations of similarly small associations.

A meta-meta-analysis provides a complementary approach by statistically synthesising estimates across existing meta-analyses to examine the extent to which quantitative findings converge despite methodological heterogeneity. Quantifying primary-study overlap further allows us to assess whether such convergence may simply reflect repeated synthesis of the same underlying studies.

Bidirectional Relationship

The mixed and often small effects reported across reviews may partly reflect that social media use and mental health are not unidirectionally related. Drawing on communication science, "transactional media effects" models[22–24] propose that media use and its psychological consequences are components of reciprocal processes. The Reinforcing Spirals Model[24] (Slater, 2007), in particular, holds that media selection and media effects feed back on one another, such that use and its psychological consequences become mutually reinforcing over time. This framework motivates examining both causal directions rather than assuming a single pathway. From the direction of social media to mental health, adolescent-specific developmental characteristics amplify vulnerability[25]. Three types of mechanisms might explain this direction[26]. First, behavioural mechanisms, such as risky posting and inauthentic self-presentation, might be associated with cyberbullying. Second, cognitive mechanisms, including upward social comparison facilitated by quantifiable metrics (e.g., like and follower counts) and algorithmically personalised content feeds, might be correlated with dissatisfaction with life and addictive social media use. Finally, neurobiological susceptibility during a period of heightened reward sensitivity and stress reactivity contributes to adolescents' digital stress to be always available online.

Conversely, existing mental health difficulties likely shape how adolescents use social media. Consistent with mood congruency theory[27], adolescents experiencing depression or anxiety engage in more frequent social comparisons and reassurance-seeking online than those without such difficulties. Poor mental health may also drive compensatory or maladaptive coping

— such as withdrawing from offline rewarding activities while increasing passive social media consumption — potentially reinforcing cycles of negative affect[28]. These reciprocal dynamics suggest that it is meaningful to examine both directions in this review.

Potential Moderators: Age and Gender

Beyond the overall association, age and gender are two moderators that may shape the relationship between adolescents' social media use and mental health. These two moderators are especially important for adolescents because of the developmental sensitivity windows[29] for age and gendered patterns of social comparison or platform use. With respect to age, the evidence is mixed: some studies suggest that social media use increases anxiety among older adolescents while reducing it among younger individuals[30], whereas others report that older users[31] experience less mental ill-being overall.

Findings on gender are similarly inconsistent. Multiple studies have found that social media disproportionately harms girls, with stronger associations with depression[32], emotional distress[33], and reduced well-being[34] compared to boys. Other work reports null effects of gender on the social media-mental health relationship[35]. Given this conflicting evidence, the present meta-meta-analysis examines whether age and gender moderate the association between social media use and adolescent mental health.

The Current Study

The present meta-meta-analysis quantitatively examines associations between social media use and mental health problems among adolescents aged 10-19 years. Although previous meta-analyses have reached differing conclusions about this relationship, it remains unclear whether these differences reflect genuinely inconsistent quantitative evidence or different interpretations of broadly similar effects. We synthesised existing meta-analyses investigating general social media use and negative mental health outcomes, including depression, anxiety, internalising symptoms, and general mental health problems, to assess the extent to which their quantitative estimates converge. In addition to estimating an overall pooled association, we assessed methodological quality and quantified overlap among reviews, allowing us to determine whether convergence across reviews reflects repeated synthesis of the same underlying studies. Finally, based on the included meta-analyses, we extracted longitudinal primary studies and conducted a complementary longitudinal meta-analysis to examine the temporal interpretation of the review-level evidence, specifically whether prospective associations were evidence in one or both temporal directions. By quantitatively integrating existing review evidence, this meta-meta-analysis aims to clarify the extent of convergence in the quantitative evidence, distinguish this convergence from differences in how small associations are interpreted, and clarify the temporal pattern represented within the existing review literature.

Methods

Information Sources and Search Strategy

This meta-meta-analysis aimed to synthesise existing meta-analyses on the use of social media among children and youths aged 10-19. A comprehensive search was conducted across multiple databases: PubMed, Scopus, PsycINFO, ERIC, EBSCOhost (including CINAHL Complete, Communication and Mass Media Complete, and Social Science Abstracts), ProQuest Dissertations and Theses Global, and Web of Science. Searches were last updated on 13 March 2026, including forward citation tracking of the seven included meta-analyses, which did not identify additional eligible studies. Full search strategies for each database are provided in the Supplementary Materials (Table A). The study selection process is shown in the PRISMA flow diagram (Figure 6).

Eligibility Criteria

Inclusion criteria for included meta-analyses were defined according to population, exposure, outcomes, and study design.

Population: Meta-analyses were included if they examined children and youths aged 10-19 years, consistent with the World Health Organization definition of adolescence[4]. Mean sample age was used as the primary indicator of eligibility; where mean age was not reported, we used the midpoint of the age range. Reviews were excluded if they focused solely on adult or university populations. We added meta-analyses of mixed populations if we can extract subgroup effect sizes among the adolescent age group[36].

Exposure: Meta-analyses were included if they examined social media use, including general, excessive, or problematic use. Reviews were excluded if they focused only on broader technology use without specific reference to social media platforms.

Outcomes: Meta-analyses were included if they reported mental health outcomes such as depression, anxiety, or internalising and externalising behaviours. Reviews focusing exclusively on well-being or other positive indicators of mental health were excluded, as the present review focused specifically on mental health problems rather than positive dimensions of mental well-being. Meta-analyses with aggregate effect sizes mixing relevant and irrelevant outcomes were also excluded: for example, one meta-analysis was excluded for reporting aggregate correlation for mental health and substance use, eating disorders, sleep disorders, as well as digital aggression[37].

Study Design: Only meta-analyses of observational studies that examined the relationship between social media use and mental health outcomes were included. Reviews that combined qualitative and quantitative findings were eligible if meta-analysis was reported separately. Intervention reviews, along with qualitative, scoping, or umbrella reviews were excluded.

Screening and Study Selection

The search identified a total of 8,780 records. Following deduplication, 4,480 unique records remained. All records were imported into ASReview, a machine learning–assisted

screening tool used to prioritise studies by predicted relevance. The default setting was used: Naïve bayes classifier, certainty-based query, and tf-idf feature extraction technique. The team conducted the pre-screening collaboratively. Titles and abstracts were reviewed iteratively in the order prioritised by ASReview until ten consecutive records were excluded as irrelevant, which served as the stopping criterion for active screening. In total, 81 records were screened with 16 marked as relevant. Following completion of active screening, the full relevance-ranked list generated by ASReview was inspected to determine a conservative threshold for subsequent conventional screening. Records ranked below position 109 were consistently unrelated to the target review design, particularly meta-analyses relevant to the review question; therefore the top 109 records were retained for screening in Covidence. As an additional safeguard against erroneous exclusion, a random 10% sample of excluded records ranked below this threshold was manually checked; no false negatives were identified.

Following this pre-screening phase, two independent reviewers (CT and YS) screened the 109 records against the predefined eligibility criteria (Proportionate Agreement = 89.91% ;Cohen's Kappa = 73.94%). Any disagreements were discussed, and unresolved cases were referred to a third reviewer (QY) for consensus.

After title and abstract screening, 24 studies were retained for full-text assessment. The same screening procedure was applied at the full-text stage, with the same dual-review procedure. Ultimately, seven studies met all inclusion criteria and were included in the final synthesis (Figure 6).

Data Extraction

Data were extracted using a piloted data extraction form by one reviewer and independently cross-checked by a second reviewer. Two levels of information were recorded.

First, we extracted information about each meta-analysis itself, including study details (authors, publication year, journal source), study design, and databases searched. We also recorded methodological features such as inclusion criteria, preregistration status, risk of bias, quality assessments, and the availability of data.

Second, we extracted information from within each meta-analysis, based on the data originally synthesised by its authors. This included the total number of primary studies, sample characteristics (age, sample size, and population type), the conceptualisation of social media use (for example, frequency or duration), target outcomes, effect size metrics (for example, Cohen’s d or odds ratios), and heterogeneity statistics. Where reported, we also extracted details of publication bias checks and subgroup analyses (for example, moderators such as gender, age, or region).

Finally, we summarised the key findings of each meta-analysis, focusing on the reported relationships between social media use and mental health outcomes. All extracted effect sizes were converted to a common metric for subsequent analysis (described in the following section).

Statistical Analysis

Analyses were conducted in R using the metafor[38], clubSandwich, robumeta, and *weightr* packages. Review-level and effect-size-level datasets were first cleaned by removing records with missing study identifiers or marked for exclusion, and then merged by study. Effect sizes, confidence interval bounds, and moderator variables were converted to numeric format. Rows with missing effect sizes, incomplete confidence intervals, invalid interval bounds, or non-positive sampling variances were excluded prior to analysis.

Sampling variances were derived from reported 95% confidence intervals. Specifically, the standard error was calculated as (upper CI−lower CI)/(2 × 1.96), and the variance was defined as the squared standard error[39].

Because multiple effect sizes were often extracted from the same meta-analysis (e.g., different mental health outcomes), statistical dependence was addressed using a multilevel random-effects model fitted with the rma.mv function in the metafor package. A three-level structure was specified, with effect sizes nested within meta-analyses. A block-diagonal sampling variance–covariance matrix was constructed assuming a within-meta-analysis correlation of $r = .80$. Models were estimated using restricted maximum likelihood (REML), and statistical inference was based on t-tests. To further account for dependence and small-sample bias, cluster-robust variance estimation with CR2 corrections and Satterthwaite-adjusted degrees of freedom was applied at the meta-analysis level using the clubSandwich package.

As a complementary approach, robust variance estimation models were fitted using the robumeta package (*robu*), again assuming a within-study correlation of $\rho = .80$. These models were used primarily for descriptive visualization (forest plots) and to assess the robustness of the overall effect estimates.

For the complementary longitudinal meta-analysis, moderator analyses were conducted using mixed-effects multilevel meta-regression models. Continuous moderators were grand-mean centered prior to analysis, and categorical moderators were examined using factor coding to obtain subgroup marginal means. In cases where moderator data were incomplete or unstable, specific meta-analyses were excluded from moderator models to ensure model convergence and interpretability. Between-study heterogeneity was summarized using a 95% prediction interval calculated from the estimated variance components of the intercept-only multilevel model.

Publication bias was assessed using multiple complementary approaches. First, funnel plots, including contour-enhanced funnel plots, were visually inspected using the *metafor* package. Second, selection models were applied using both the *weightfunct* function from the *weightr* package[40] and the selmodel function in *metafor*, specifying step-function weight models based on statistical significance thresholds (e.g., $p < .025$). Two-sided p-values were computed for each effect size using its sampling variance, and alternative step specifications were examined to evaluate the robustness of the results to different assumptions about publication bias.

Corrected Covered Area

To assess the overlap of primary studies across included systematic reviews, a citation matrix was constructed with rows representing unique primary studies and columns representing reviews. The Corrected Covered Area (CCA) was calculated in accordance with Pieper et al.[41] as (N − r) / (r × c − r), where N is the total number of included study occurrences (including double counting across reviews), r is the number of unique primary studies, and c is the number of reviews. Given the conceptual and population heterogeneity across reviews, the CCA was used descriptively to characterise overlap rather than to inform quantitative adjustment. Overlap was interpreted using thresholds proposed by Pieper et al. (0–5% slight, 6–10% moderate, 11–15% high, and >15% very high overlap). Pairwise overlap between reviews was additionally explored by calculating the number of shared primary studies for each review pair and visualised using a heatmap.

Quality Assessment

The methodological quality of the included studies was appraised by two authors (CT and YS) using the JBI Critical Appraisal Instrument for Systematic Reviews and Research Syntheses[42], which evaluates methodological rigor, risk of bias, and transparency in reporting (see Table 2). This tool was used to assess the methodological quality of the included meta-analyses. Each meta-analysis was assessed against an 11-item checklist, with items rated as 'yes', 'no', 'unclear' and 'not applicable', depending on the extent to which the study satisfied each criterion.

The assessment criteria included: (1) the precision and explicit formulation of the review question; (2) the suitability of the inclusion criteria; (3) the application of rigorous and appropriate search strategies; (4) the adequacy of the sources and databases consulted to identify relevant studies; (5) the use of appropriate standards for the appraisal of studies; (6) the conduct of independent and critical appraisal processes; (7) the implementation of procedures to minimise errors in data extraction; (8) the application of appropriate methods for data synthesis; (9) the evaluation of potential publication bias; (10) the extent to which recommendations for policy and/or practice were substantiated by the reported evidence; and (11) the formulation of clear and appropriate directives for future research. Each study was assigned a quality score corresponding to the total number of "yes" responses out of the 11 criteria. To minimize the coding errors, each study was coded by two authors (CT and YS) independently. The inter-rater reliability was found to be good on average across all criteria, with $k = 0.96$ (ranging from 0.92~1.00). All disagreements were discussed until agreement was reached among the three reviewers (CT, YS, and JL).

Complementary Longitudinal Mini Meta-analysis

Within the included seven meta-analyses, to further understand the direction and the strength of the association, we filtered longitudinal primary studies included in the meta-analysis. We only included studies where the mean age is between 10 to 19 years old and reported a prospective association between social media use and mental health across at least two time points in either temporal direction: social media use at an earlier time point predicting subsequent mental health, or mental health at an earlier time point predicting subsequent social media use. The design was pre-registered on Open Science Framework before data extraction (link blinded for review). When multiple statistics were reported, Pearson's correlation coefficients (r) were prioritized because they represent zero-order associations and are directly comparable across studies. These zero-order correlations should be interpreted as measures of temporal association rather than causal effects. When correlations were not reported, standardized regression coefficients (β) were extracted and converted to r using established transformation formulas[43]. The formula is $r = 0.98\beta + 0.05\lambda$ where $\lambda = 1$ if $\beta > 0$ and $\lambda = -1$if $\beta < 0$. Cohen's d = $\frac{2r}{\sqrt{1-r^2}}$

Results

Narrative Synthesis of the Seven Included Meta-analyses

Description of Meta-analysis Characteristics

Our review included seven meta-analyses published between 2019 and 2025 (Table 1), and 3 out of 7 meta-analyses were pre-registered. Fassi et al.[14] included the largest number of studies (k = 143), whereas Nan et al.[44] and Yin et al.[45] included the fewest (k = 7 each). The participants' mean age ranges from 12.35[44] to 18.04[15]. Gender distribution was relatively balanced across the meta-analyses. The majority of the meta-analyses (n = 6) focused on both clinical and non-clinical populations. Notably, Fassi et al.[14] provided a more comparative perspective by including clinical samples, which comprised 11% of their effect sizes. No meta-analysis imposed any geographic restrictions. Figures 1a, 1b, 1c, and 1d present a descriptive distribution of the seven included meta-analyses.

Findings on the Relationship

Across the seven included meta-analyses, conclusions were broadly consistent in indicating a small association between greater social media use and poorer mental health outcomes. Four reviews, including Liu et al.[46], Fassi et al.[14], Nan et al.[44], and Ivie et al.[47], reported statistically significant but small associations with outcomes such as depression, internalising symptoms, and social anxiety. Marciano et al.[15] similarly found positive associations with ill-being, although effects varied by type of digital media use. In contrast, Ferguson et al.[12] concluded that the observed associations were too small to support claims of meaningful harm. Yin et al.[45] reported that social media use was associated with both positive and negative mental health indicators, suggesting that findings depend on how outcomes are conceptualised. Overall, while the direction of association was generally consistent, conclusions differed in terms of magnitude, interpretation, and outcome definition.

Findings on the Moderators

Findings on gender as a moderator were contradictory across meta-analyses. Liu et al.[46] reported stronger associations between social media use and negative mental health for girls (OR = 1.72) than boys (OR = 1.20). In contrast, Fassi et al.[14] and Ferguson et al.[12] found no moderating effect of gender. Marciano et al.[15] identified a significant moderating effect of gender composition, with stronger associations observed in studies with a higher percentage of male participants (β = 0.333, p = .034). Overall, evidence for gender as a moderator was inconsistent.

Findings on age as a moderator were largely non-significant across meta-analyses. Fassi et al.[14] , Ferguson et al.[12] , and Ivie et al.[47] found no moderating effect of age. Marciano et al.[15] reported a small but significant effect, with increasing age associated with stronger correlations between social media use and ill-being (β = 0.008, p = .027), although the magnitude of this

effect was minimal. Studies examining broader age comparisons reported mixed findings. Nan et al.[44] found that the association was weaker in adolescents (r = .03) compared to non-adolescents (r = .19; p = .005). In contrast, Yin et al.[45] found no significant differences in effect sizes across age groups. Overall, evidence for age as a moderator was limited and largely non-significant.

Meta-Meta-Analysis

Findings on the Relationship

Meta-meta-analysis across seven meta-analyses (k = 11 effect sizes) found a small, statistically significant association between greater adolescent social media use and more mental health problems (SMD = 0.21, SE = 0.023, p < .001, 95% CI [0.16, 0.27]). Substantial heterogeneity was reported (Q(10) = 566.98, p < .001, I^2 = 98.0%, τ^2_within = 0.006). A 95% prediction interval ranged from 0.06 to 0.36, indicating that the average association is consistently positive across contexts. Figure 2 presents the forest plot, while Figure 3 displays a heatmap of effect sizes by outcome category and meta-analysis.

Sensitivity Analysis

We conducted two sensitivity analyses to assess the robustness of the main findings. First, we excluded Fassi et al.[14] due to substantial overlap with other included meta-analyses. Specifically, this review shared a large number of primary studies with Liu et al.[46] , Ferguson et al.[12] , and Ivie et al.[47] , resulting in a slightly higher corrected covered area and raising concerns about non-independence. The results remained almost the same after exclusion (SMD = 0.20, SE = 0.03, p = .003, CR2-adjusted). Second, we excluded Marciano et al.[15] , which contributed the largest effect size in the dataset. The results again remained almost the same (SMD = 0.20, SE = 0.02, p = .002, CR2-adjusted). Taken together, these sensitivity analyses suggest that the observed effect is robust.

Publication Bias Reported by Meta-Analyses' Authors

Across meta-analyses, conclusions regarding publication bias ranged from no evidence of bias to indications of potential overestimation. Publication bias was not assessed in one meta-analysis[15]. All other reviews conducted at least one formal assessment. Fassi et al.[14] evaluated funnel plot symmetry, Egger's regression, and contour-enhanced funnel plots, reporting no evidence of publication bias. Yin et al.[45] relied on funnel plot inspection and Rosenthal's fail-safe N and likewise concluded that findings were robust to publication bias. Ivie et al.[47] reported no visual evidence of asymmetry and conducted a p-curve analysis, which was interpreted as consistent with a small but genuine effect. Liu et al.[46] reported mixed findings: Begg's test was non-significant, whereas Egger's regression indicated mild asymmetry; trim-and-fill did not impute additional studies. Ferguson et al.[12] identified statistically significant Egger's regression results and four imputed studies under trim-and-fill but interpreted these findings cautiously. In contrast, Nan et al.[44] reported evidence of asymmetry using both Egger's regression and trim-and-fill, with bias-adjusted estimates attenuating to non-significance.

JBI Quality Assessment of Meta-analyses Findings

The methodological quality was assessed using the Joanna Briggs Institute (JBI) Critical Appraisal Checklist for Systematic Reviews and Research Syntheses[42] (Table 2). Overall, the included meta-analyses demonstrated high methodological quality, with a mean score of 9.57 out of a possible 11 (range = 9–11). All seven meta-analyses satisfied the key criteria, with limitations observed regarding the procedures used to minimise errors in data extraction (2Nos,1Unclear/7Studies) and independent appraisal by two or more reviewers (3Nos/7Studies).

Corrected Covered Area

To assess overlap of primary studies across reviews, we calculated the corrected covered area (CCA). Across the seven included reviews, 220 unique primary studies were identified, with 271 total study occurrences across reviews. This resulted in a CCA of 3.9%, indicating slight overlap of primary studies across reviews (see Supplementary Figure A). Consistent with this low CCA, most primary studies appeared in only one review (n = 184, 84%), while a smaller number appeared in two (n = 24, 11%), three (n = 9, 4%), or four reviews (n = 3, 1%). Pairwise overlap between reviews was generally low.

Complementary Longitudinal Meta-analysis

We identified 96 longitudinal effect sizes from 33 independent studies examining associations between adolescents' social media use and mental health. Effect sizes came from North America (k = 50), Europe (k = 24), East Asia (k = 7), Oceania (k = 6), and other regions (k = 9). Sample sizes ranged from 72 to 4429, follow-up durations ranged from 1 to 108 months, and mean participant age ranged from 9.0 to 18.76 years. Figures 4a, 4b, 4c, and 4d present descriptive statistics of the 33 longitudinal studies.

A three-level random-effects model yielded a pooled estimate of Cohen's d = 0.24, 95% CI [0.13, 0.36], $p < .001$, indicating a small positive longitudinal association between social media use and mental health problems. Heterogeneity was substantial [$Q(95) = 8631.41$, $p < .001$, between-study $\sigma^2 = 0.108$, within-study $\sigma^2 = 0.014$, approximate $I^2 = 98.2\%$].

Bi-directional Relationship

To further clarify the longitudinal pathways, we conducted separate subgroup analyses for forward and reverse-direction effects. For the forward direction, 74 effect sizes examined whether social media use was prospectively correlated with subsequent mental health. The pooled effect was statistically significant, d = 0.25, SE = 0.06, 95% CI [0.12, 0.37], $p < .001$. This indicates that higher social media use was associated with poorer subsequent mental health. Heterogeneity was substantial, $Q(73) = 8362.37$, $p < .001$.

For the reverse direction, 22 effect sizes examined whether mental health was prospectively correlated with subsequent social media use. As compared to forward direction (d = 0.25), the pooled effect for reverse direction was slightly less in magnitude, d = 0.18, SE =

0.04, 95% *CI* [0.10, 0.27], $p < .001$. Heterogeneity was again substantial, $Q(21) = 195.56$, $p < .001$.

Thus, statistically significant prospective associations were observed in both temporal directions. Although reverse-direction effects appeared smaller descriptively, readers need to take note of the smaller number of reverse-direction effects. Forest plots for the forward (social media → mental health) and reverse (mental health → social media) directions are presented in Figures B and C respectively (Supplementary Materials).

Moderators

In the revised four-moderator meta-regression model, which included temporal direction, follow-up duration, mean age, and proportion of female participants, the omnibus test of moderators was not statistically significant, $Q(4) = 1.98$, $p = .740$. None of the individual moderators reached statistical significance. Temporal direction was not significant, $\beta = 0.01$, $SE = 0.05$, 95% *CI* [−0.08, 0.10], $p = .827$, indicating that reverse-direction associations did not significantly differ from forward-direction associations after accounting for the other moderators. Although the reverse-direction pooled estimate was descriptively smaller than the forward estimate, temporal direction did not significantly moderate effect size in the meta-regression. The apparent difference in magnitude should therefore not be interpreted as evidence that one direction is reliably stronger than the other.

Follow-up duration was also not significant, $\beta = 0.002$, $SE = 0.002$, 95% *CI* [−0.003, 0.007], $p = .408$. Similarly, mean age, $\beta = 0.004$, $SE = 0.04$, 95% *CI* [−0.07, 0.08], $p = .905$, and proportion of female participants, $\beta = -0.09$, $SE = 0.08$, 95% *CI* [−0.25, 0.07], $p = .275$, showed no clear moderating role. Residual heterogeneity remained statistically significant, $Q(84) = 6889.63$, $p < .001$, suggesting that substantial variability in effect sizes remained unexplained. Taken together, these moderator analyses did not provide evidence that temporal direction, follow-up duration, mean age, or gender composition systematically explained variation in effect sizes. Figures 5a and 5b present bubble plots of effect sizes by follow-up duration and mean age, respectively.

Publication Bias

We assessed publication bias using three approaches. The funnel plot (Supplementary Figure E) was wide but broadly symmetric, suggesting lack of publication bias. Egger' test is not significant (b = −1.64, SE = 2.25, p = .47), indicating no evidence of small−study effects. However, a Vevea−Hedges three−parameter selection model yielded a significant likelihood−ratio test, $\chi^2(1) = 7.88$, p = .005, and an adjusted mean that attenuated to non−significance (b = −0.03, 95% CI [−0.32, 0.26]). This suggests that selective publication may have inflated the observed

effect. Given this divergence and the very high heterogeneity ($Q = 8621.5$, $p < .001$), which limits the power of all bias diagnostics, results should be interpreted cautiously, with the true effect bracketed by the adjusted and unadjusted estimates.

Discussion

Summary of Findings

This pioneering meta-meta-analysis examined associations between adolescent social media use and mental health problems, alongside a mini-meta-analysis of longitudinal primary studies. Across both levels of quantitative syntheses, findings converged on a broadly similar conclusion: greater social media use was slightly associated with poorer mental health outcomes. The longitudinal synthesis further suggested prospective correlations in both temporal directions. Moderator findings across the included meta-analyses were inconclusive, whereas the present longitudinal meta-regression provided little evidence that age or gender composition systematically explained heterogeneity.

A Small but Statistically Significant Association Between Social Media Use and Poorer Mental Health

The meta-meta-analysis of seven reviews demonstrated a small but statistically significant association between greater adolescents' social media use and poorer outcomes such as depression, internalising symptoms, social anxiety, ill-being, and general mental health problems. Importantly, despite substantial methodological heterogeneity across reviews, the direction of findings was relatively consistent. This suggests that disagreement within the literature[12,13] may concern interpretation more than the existence of an association itself.

A major debate within the literature concerns how these small associations should be interpreted. For example, Ferguson et al.[12] reported a weighted average correlation of 0.06 ($p < .001$) yet concluded that the association was not meaningful, whereas Fassi et al.[14] reported a similarly small weighted average correlation of 0.08 ($p < .001$) but interpreted it as evidence of a significant relationship. These contrasting conclusions appear to reflect differences in interpretive frameworks, particularly the distinction between statistical significance and practical or clinical significance, rather than fundamentally contradictory evidence.

The present synthesis cannot determine whether an association of this magnitude should be regarded as clinically or practically meaningful. Rather, it clarifies that some apparent disagreement in the literature occurs at the level of interpretation despite broadly similar small quantitative associations.

The low degree of primary-study overlap provides further context for this convergence. Although the seven meta-analyses addressed closely related substantive questions, a large proportion of primary studies appeared in only one review, resulting in a low CCA. Thus, convergence in the direction of review-level estimates cannot simply be attributed to repeated synthesis of the same primary studies. Instead, broadly similar small associations emerged across reviews drawing largely on distinct evidence bases. The limited overlap likely reflects

differences in outcome domains, operationalisations of social media use, age criteria, search periods, and other eligibility criteria. Nevertheless, low CCA should not be interpreted as evidence of methodological independence, given the substantial conceptual and methodological heterogeneity across reviews.

Prospective Correlations Were Observed in Both Temporal Directions

Although some primary studies included within the reviewed meta-analyses used longitudinal designs, the effect sizes synthesised by those meta-analyses were predominantly based on concurrent cross-sectional associations. Consequently, conclusions regarding temporal direction or causality remained limited within the existing review literature. Our complementary longitudinal meta-analysis of longitudinal primary studies partially addressed this limitation by examining prospective correlations over time.

The longitudinal synthesis echoed the meta-meta-analytic result: a modest yet reliable prospective link emerged. What stood out, however, was that the relationship ran in both directions. Greater social media use was prospectively associated with poorer subsequent mental health, and conversely poorer mental health was prospectively associated with greater use down the line. Such mutual patterning fits a reciprocal account far better than any unidirectional story in which the platform alone drives adolescent wellbeing.

These findings broadly align with transactional media effects frameworks, which conceptualise media use and psychological outcomes as mutually influencing processes rather than simple cause-and-effect relationships[22–24]. On one hand, social media experiences such as cybervictimisation, upward social comparison, and exposure to appearance-focused content may contribute to later distress[26]. On the other hand, adolescents experiencing depression or anxiety may increasingly engage in reassurance-seeking, social comparison, or compensatory social media use as a coping strategy, consistent with mood-congruency theory and compensatory use perspectives[27].

The bidirectional pattern also aligns with the reinforcing spirals model[24], which proposes that media selection and media effects may reinforce one another over time. Readers should note that these findings are compatible with reciprocal theoretical accounts but do not constitute a direct test of reciprocal causal mechanisms. In addition, the substantial heterogeneity observed across studies suggests that these processes are unlikely to operate uniformly across adolescents. Rather, the mental health consequences of social media use may depend on individual vulnerabilities, online experiences, and broader social contexts[16,17].

Gender Differences Were Inconsistent Across Studies

Evidence regarding gender differences was inconsistent across reviews and longitudinal studies. Variation in sample composition may partly explain these inconsistencies. Female representation varied substantially across the longitudinal studies, ranging from balanced samples to entirely female cohorts. Differences in social media behaviours may also contribute to heterogeneous findings. For example, girls may engage more frequently in appearance-based

social comparison[48,49] and emotionally expressive online interactions, whereas boys may participate differently in online gaming communities or digital peer networks. However, the overall evidence does not support a clear or universal conclusion that one gender is consistently more vulnerable than the other. This heterogeneity may reflect differential susceptibility to media effects, whereby the impact of social media varies according to individual and contextual factors rather than affecting all adolescents uniformly[23].

Younger Age Within Adolescence Did Not Predict Stronger Social Media–Mental Health Associations

The present findings provided limited evidence that younger adolescents experienced substantially stronger associations between social media use and poorer mental health within adolescent populations. Across reviews, age moderation effects were largely non-significant, and the longitudinal bubble plots showed little clear age-related pattern in the social media-to-mental health pathway.

These findings should be interpreted cautiously and specifically within the context of social media–mental health associations among adolescents. The present review does not address whether adolescents are more vulnerable than adults, nor does it evaluate broader forms of online risk or digital harm. Younger adolescents may still differ in their susceptibility to other online experiences, including cybervictimisation, harmful content exposure, privacy risks, or exploitative platform features[50].

Nevertheless, the present findings do not provide strong evidence that younger adolescents consistently show stronger negative associations between social media use and mental health compared with older adolescents. Recent policy discussions have frequently focused on age-based restrictions and social media bans for younger users. However, the present evidence suggests that variability in adolescent outcomes may depend more on contextual and individual factors than on chronological age alone.

This interpretation aligns with Livingstone and Sylwander[51], who argued that there is no singular "right age" at which digital technologies become uniformly harmful or safe for children and adolescents. Rather than assuming that younger age automatically confers greater vulnerability, future policy and research may benefit from considering developmental differences, online experiences, family environments, platform design, and safety mechanisms more carefully.

Current Measures of Social Media Use May Oversimplify Adolescents' Digital Experiences

A broader issue across the literature concerns how social media use itself is conceptualised and measured. Most studies operationalised social media exposure using self-reported time spent online, despite growing recognition that duration-based measures may inadequately capture adolescents' actual digital experiences. Two adolescents reporting similar levels of social media use may nevertheless encounter very different online environments,

ranging from supportive peer interaction[52] to harmful social comparison or exposure to distressing content.

This limitation may partly explain the substantial heterogeneity observed across studies. Factors such as viewed content, motivations for use, active versus passive engagement, and platform-specific experiences may shape whether social media experiences become beneficial, neutral, or harmful. Consequently, social media use cannot be understood as a single uniform behaviour with universally consistent effects[53,54].

Importantly, social media may also provide meaningful benefits for some adolescents, including opportunities for social connection, emotional support, and access to peer communities, particularly for those experiencing social isolation offline. These potential benefits further highlight why adolescent social media use cannot be understood solely through a harm-focused framework[54]. As Boyd[55] argues in It's Complicated: The Social Lives of Networked Teens, adolescent digital life is shaped by broader social, developmental, and contextual factors rather than by technology alone.

Longitudinal Evidence Base Was Concentrated in Western Contexts

Most longitudinal studies included in the present synthesis were conducted in North America and Europe. Since culture fundamentally shapes how people connect on social media, the current evidence base may not fully generalise across different socio-cultural environments. Adolescents' social media experiences are shaped by broader social contexts, including platform availability, parental monitoring practices, and cultural norms surrounding peer relationships and emotional expression[55–57].

Cross-cultural differences in dominant platforms and online norms may further contribute to variability in adolescents' digital experiences. For example, adolescents in China may primarily use WeChat or Xiaohongshu, whereas adolescents in many Western contexts more commonly use Instagram, Snapchat, or WhatsApp. Emerging evidence suggests that associations with mental health may differ across platforms and adolescents[58,59]. Cultural differences may additionally shape how mental distress is experienced and expressed online[60,61], thus potentially contributing to the heterogeneity observed across studies.

Publication Bias and Methodological Limitations Remain Important Concerns

Although most included meta-analyses formally assessed publication bias, evaluation relied almost exclusively on conventional funnel plot–based methods, including visual inspection, Egger's and Begg's regression tests, trim-and-fill procedures, and fail-safe N calculations. None implemented selection or weight-function models.

Funnel plot asymmetry tests have recognised limitations, particularly in the presence of small effect sizes and substantial heterogeneity. They are often underpowered, rely partly on subjective interpretation, and do not explicitly model the publication process. Recent methodological guidance recommends supplementing or replacing these approaches with selection models, which more directly model publication mechanisms and better accommodate

heterogeneity[62]. Given that pooled associations in this literature are small, even modest selection effects could meaningfully influence estimates, and the possibility of publication bias cannot be ruled out entirely.

More broadly, several methodological limitations within the evidence base also warrant consideration. Methodological quality across the included reviews was generally high according to the JBI appraisal tool. Nevertheless, only a minority of reviews pre-registered their protocols, indicating room for improvement in transparency, reproducibility, and protection against selective reporting. Furthermore, much of the existing review literature remains dominated by cross-sectional associations, limiting stronger conclusions regarding temporal ordering and causal mechanisms.

Important Mental Health Outcomes Remain Understudied

Several theoretically and clinically important outcomes appeared less frequently within the reviewed meta-analyses, including loneliness, externalising problems, suicidal ideation, self-harm, and emotion regulation difficulties. Greater attention to these outcomes may provide a more comprehensive understanding of how social media use relates to adolescents' broader psychological and behavioural functioning[26], particularly given increasing public concern surrounding emotional dysregulation and self-harm among young people.

The present review also focused primarily on negative mental health outcomes and therefore did not examine positive aspects such as well-being and life satisfaction. Considering such outcomes in future syntheses could complement symptom-based findings and provide a more comprehensive picture of adolescent mental health. Moreover, social media use may also relate to other outcomes and beneficial aspects such as social support, peer connection, identity exploration, and access to online communities[63].

Implications for Policymakers, Educators, Parents, and Designers

Policymakers

The present findings should not be interpreted as evidence either for or against particular age-based restrictions. Rather, the moderator analyses provide limited evidence for identifying a specific age within adolescence at which the association between social media use and poorer mental health becomes substantially stronger. Although small associations with poorer mental health were consistently observed, there was limited evidence that younger adolescents consistently showed stronger negative associations than older adolescents. Policymakers may therefore benefit from considering more balanced approaches involving social media safety education[64,65], online safety protections[66], and platform accountability alongside age-appropriate safeguards.

Educators and Schools

Schools play an important role in supporting adolescents' digital literacy and online well-being. Educational approaches may benefit from helping adolescents critically evaluate online content, recognise harmful online interactions, manage social comparison processes, and protect online privacy[67]. Schools may also provide important opportunities for early identification and support for adolescents experiencing distress related to online experiences.

Parents and Caregivers

For parents and caregivers, the findings suggest that focusing exclusively on total time spent on social media use may be insufficient[68]. Greater attention may instead be directed toward understanding how adolescents engage with social media and what content they encounter. Open and regular conversations, pre-negotiated rules, and collaborative discussions regarding positive as well as negative online experiences may therefore be more constructive than purely restrictive monitoring approaches.

Platform Designers and Technology Companies

The findings also have implications for platform designers and technology companies. Engagement-driven design features, appearance-focused content, and algorithmically amplified harmful material may contribute to problematic online experiences for some adolescents[69]. Safer platform architectures, stronger moderation systems[70], transparent recommendation practices, and improved protections for vulnerable teenage groups may help reduce harmful experiences while preserving opportunities for social connection and support.

Strengths, Limitations, and Future Directions

To our knowledge, it is among the first quantitative meta-meta-analyses synthesising meta-analytic evidence on adolescent social media use and mental health. This merit is further complemented with longitudinal synthesis, overlap assessment across reviews, and systematically-evaluated methodological quality.

Several limitations should nevertheless be acknowledged. First, substantial heterogeneity was observed across reviews and longitudinal studies, highlighting that the association might differ significantly across individuals and contexts. Second, most studies relied on adolescents' self-reported estimates of social media use, which might suffer from recall bias and measurement error. In addition, much of the available evidence was derived from North American and European samples, potentially limiting generalisability to adolescents in other sociocultural and technological contexts. Moreover, the mini-meta-analysis findings should be interpreted cautiously. Most longitudinal effect sizes were based on zero-order correlations and unadjusted prospective associations that did not account for baseline levels of social media use or mental health. In addition, these longitudinal studies varied in their analytic approaches, including prospective zero-order associations, conventional cross-lagged models, and within-person models. Consequently, the present findings are consistent with reciprocal temporal associations but do not establish causal relationships and the inferences should be limited to within-person

processes. Finally, because the included studies spanned rapidly evolving social media environments across nearly two decades, the findings may not fully reflect adolescents' current digital experiences and platform ecosystems.

Several priorities for future research emerge from the present findings. First, improved measurement approaches are needed. Future research would benefit from incorporating objective behavioural measures of digital engagement alongside self-report data[71,72]. The present findings also highlight the need for more nuanced conceptualisations of social media use beyond self-reported screen-time measures[17,20]. Future studies should examine how adolescents use social media, including content consumption, active versus passive engagement[73], social comparison processes, motivations for use[74], and platform-specific behaviours.

Second, stronger study designs are needed to clarify developmental processes and temporal relationships, including more longitudinal, within-person, and experimental designs. Future syntheses would benefit from focusing on baseline-adjusted longitudinal estimates, including cross-lagged and within-person models, to clarify the developmental processes linking adolescent social media use and mental health.

Third, greater attention should be given to diversity and breadth of outcomes. Future research should include more underrepresented regions and adopt more culturally sensitive approaches to understand adolescent social media use across diverse platform ecosystems. Future research would also benefit from examining both positive and negative dimensions of adolescent digital life to better capture the complexity of social media experiences across different contexts and populations. Finally, greater methodological transparency, including preregistration and open data practices, would further strengthen the evidence base.

Conclusion

Overall, the present meta-meta-analysis provides evidence for a small but consistent association between adolescent social media use and poorer mental health outcomes. Longitudinal findings further suggest prospective correlations in both temporal directions, although causal conclusions remain limited. Rather than supporting simplistic narratives of universal harm, the findings point toward a more complex and heterogeneous relationship shaped by individual, contextual, and methodological factors. Balanced and evidence-informed approaches are therefore needed in future research, policy, and practice concerning adolescents' digital lives.

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Ethical Approval and Informed Consent: This article does not contain any studies with human participants performed by any of the authors

Data availability: The data that support the findings of this study are available in both supplementary materials and this public link: https://github.com/qiyangzh/SocialMediaYouthMentalHealthMeta

Table 1. Characteristics of the seven included meta-analyses.

Study	Journal	Sources searched	Sample Age (M)	Sample size	Female Number (%)	Sample type	Study design	Years of studies searched	Number of studies	Social Media	Target Mental Health Outcomes	Publication Bias Tests Used	Effect Sizes
Liu et al. 2022	International Journal of Environmental Research and Public Health	3: PubMed, PsycINFO, Web of Science	10–19 (14.42)	55340	2837 (51.26)	General population	Cross-sectional or longitudinal	Up to January 9, 2022	26	Time Spent on Social Media (TSSM)	Depression	Begg's test; Egger's test; Funnel plot; Trim-and-fill	Depression(*OR* = 1.60), Girls (*OR* = 1.72), boys (*OR* = 1.20)
Fassi et al. 2024	JAMA Pediatrics	5: MEDLINE, Web of Science, PsycINFO, Scopus, Europe PubMed Central; Citation tracking	10–24 (15.11)	1094890	559598 (51.11)	Both analyzed; 11% of effect sizes from clinical samples	Cross-sectional or longitudinal	2007–2023	143	Time spent and user engagement	Internalizing symptoms: anxiety, depression	Egger's test; Funnel plot	Time spent (clinical, *r* = .08) ; Engagement (clinical, *r* = .12)
Nan et al. 2024	Mass Communication & Society	6: PubMed, MEDLINE, IEEE Xplore, PsycINFO, Scopus, ProQuest ; Citation tracking	10-19 (12.35)	4701	2382 (50.66)	General population	Cross-sectional or longitudinal	Up to March 5, 2023	7	Social media use (time, frequency, intensity across platforms)	Social anxiety (including social phobia, communication anxiety)	Egger's test; Funnel plot; Trim-and-fill	*r* = .03

Marciano et al. 2022	Front Public Health	7: ERIC, ProQuest Sociology, Communication & Mass Media Complete, Psychology and Behavioral Sciences Collection, PsycINFO, CINAHL, PubMed, Web of Science	9.50–25.5 (18.14)	217034	132456(61.03)	General population	Cross-sectional or longitudinal	Up to September 2021	23	Social media use, digital media addiction, screen time	Ill-being, Covid-19-related stress	Not provided	ill-being and social media use (r = .171); Percentage of males in the sample (β = 0.333); Age (β = 0.008)
Ivie et al. 2020	Journal of Affective Disorders	3: PsycNET, PubMed, Web of Science; Handsearch	11–18 (15.42)	92371	46860 (50.73)	General population	Cross-sectional, longitudinal	Up to January 17, 2020	12	Time spent using social media	Depressive symptoms	Funnel plot; p-curve analysis	Depressive symptoms (r =.12)
Ferguson et al. 2025	Professional Psychology: Research and Practice	2: APA PsycInfo, MEDLINE	12–18 (15.23)	2711028	1365274 (50.36)	General population	Cross-sectional and longitudinal design	2012 to September 2022	46	Time spent on social media	Depression, anxiety, suicidal ideation	Egger's regression; Funnel plot; Trim-and-fill	β = .061

Yin et al. 2019	Social Science Computer Review	5: Web of Science, Elsevier SDOL, Springer, PsycINFO, Google Scholar	≤ 18 (15.45)	5522	3107 (56.26)	General population	Cross-sectional (with one experimental study with correlation coefficient)	2005 to December 2016	7	Social networking sites usage	Loneliness, Depression	Funnel plot	Positive indicators of mental health (r = .045); negative indicators of mental health (r = .061)

Note. M = mean age of participants (years). % = percentage of female participants in the sample. *OR* = odds ratio. r = Pearson correlation coefficient. β = standardised regression coefficient. TSSM = time spent on social media.

Table 2. Methodological quality assessment of the included meta-analyses by record according to the JBI critical appraisal of systematic reviews and research synthesis

Author, year	Clear review question?	Appropriate inclusion criteria?	Appropriate search strategy?	Adequate use of sources?	Appropriate appraisal criteria?	Appraisal by two or more reviewers?	Methods to minimise error in data?	Appropriate method to combine studies?	Assessed publication bias?	Appropriate recommendations?	Appropriate new research directives?	Overall appraisal score (total 11)
Fassi et al., 2024	Y	Y	Y	U	Y	Y	Y	Y	Y	Y	Y	10
Ferguson et al., 2025	Y	Y	Y	N	Y	N	Y	Y	Y	Y	Y	9
Ivie et al., 2020	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	10
Liu et al., 2022	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	11
Marciano et al., 2022	Y	Y	Y	Y	Y	Y	N	Y	N	Y	Y	9
Nan et al., 2024	Y	Y	Y	Y	Y	N	U	Y	Y	Y	Y	9
Yin et al., 2019	Y	Y	Y	Y	N	N	Y	Y	Y	Y	Y	9

Note. Y = Yes, N = No, U = Unclear, NA = Not Applicable.

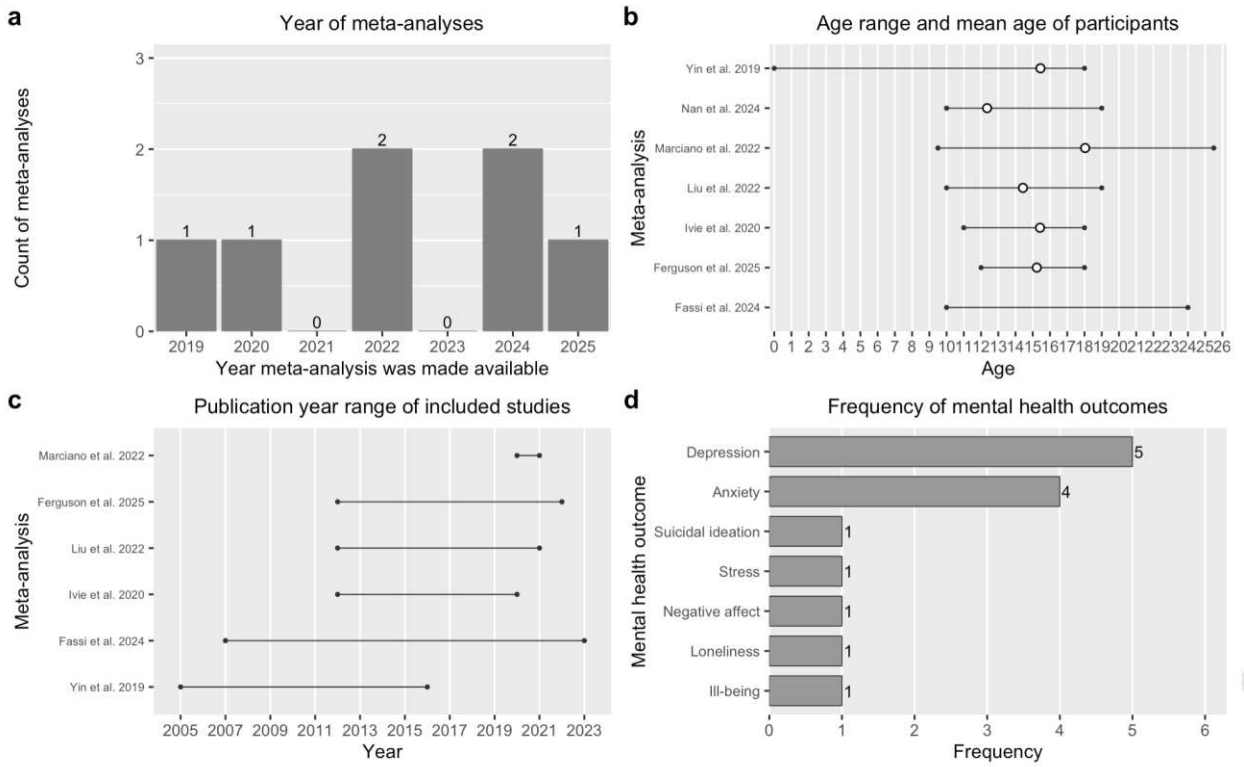


Figure 1. Characteristics of the included meta-analyses. a, Histogram of publication years of the included 7 meta-analyses. **b**, Age range and mean age of the participants in the 7 included meta-analyses. *Note*. Fassi et al. (2024) did not report the mean age. **c**, The publication year range of the included 7 meta-analyses. **d**, Frequencies of mental health outcomes were examined in the 7 included meta-analyses.

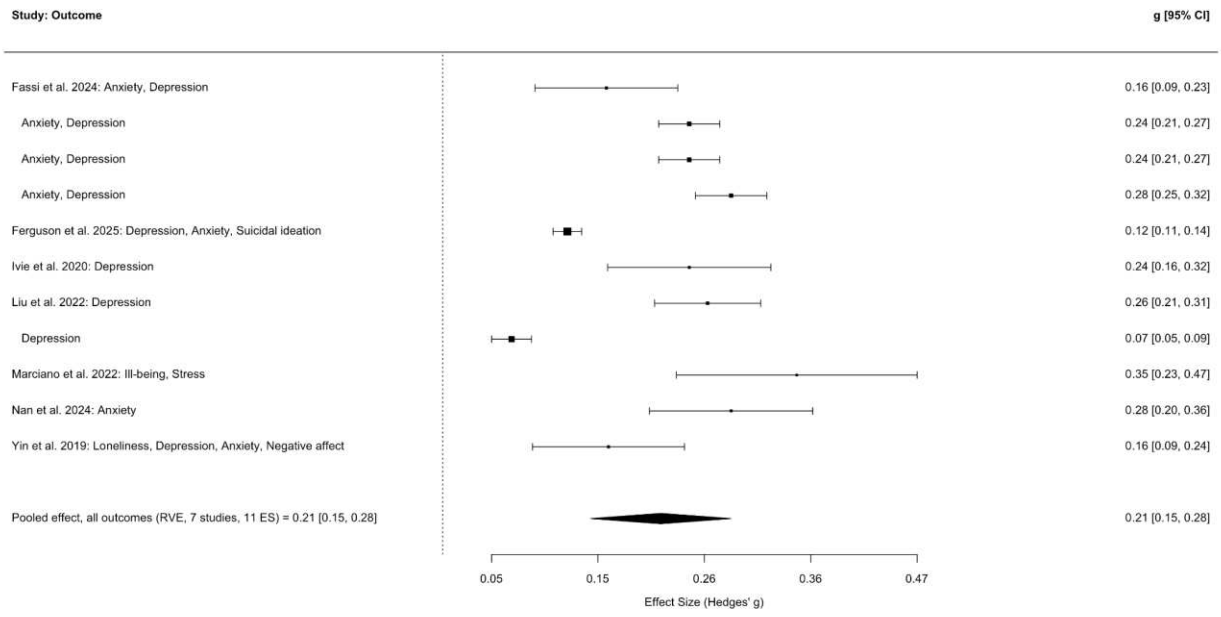


Figure 2. Forest plot of 7 meta-analyses

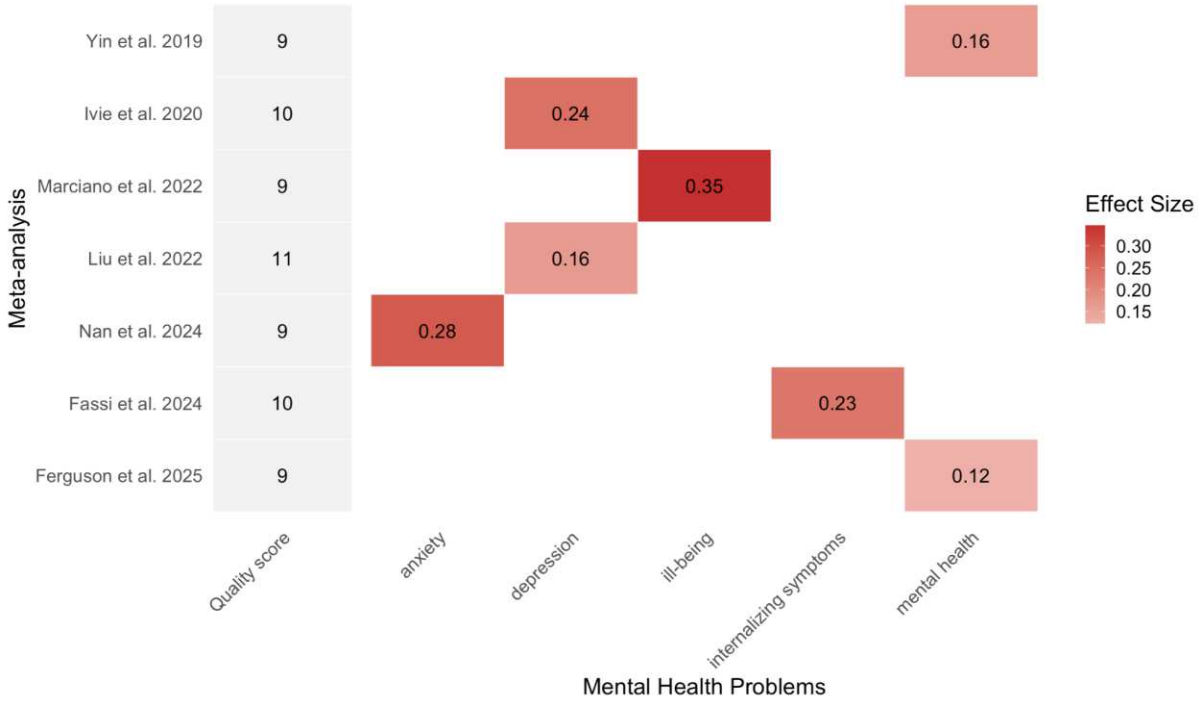


Figure 3. Heatmap of effect size by outcome category and study. Studies were ordered chronologically to show the changes in effect sizes over the past six years from 2019 to 2025. Each cell shows one review-level pooled effect size (Cohen's d). Positive values indicating greater social media use associated with poorer mental health, positioned by the contributing meta-analysis (row) and its outcome category (column). Cell colour intensity scales with effect magnitude; blank cells indicate that the meta-analysis did not report a pooled estimate for that outcome. Red represents positive correlation between social media usage and mental health. The darker the color, the larger the correlations. The left column reports each meta-analysis's quality score computed from JBI critical appraisal of systematic reviews and research synthesis.

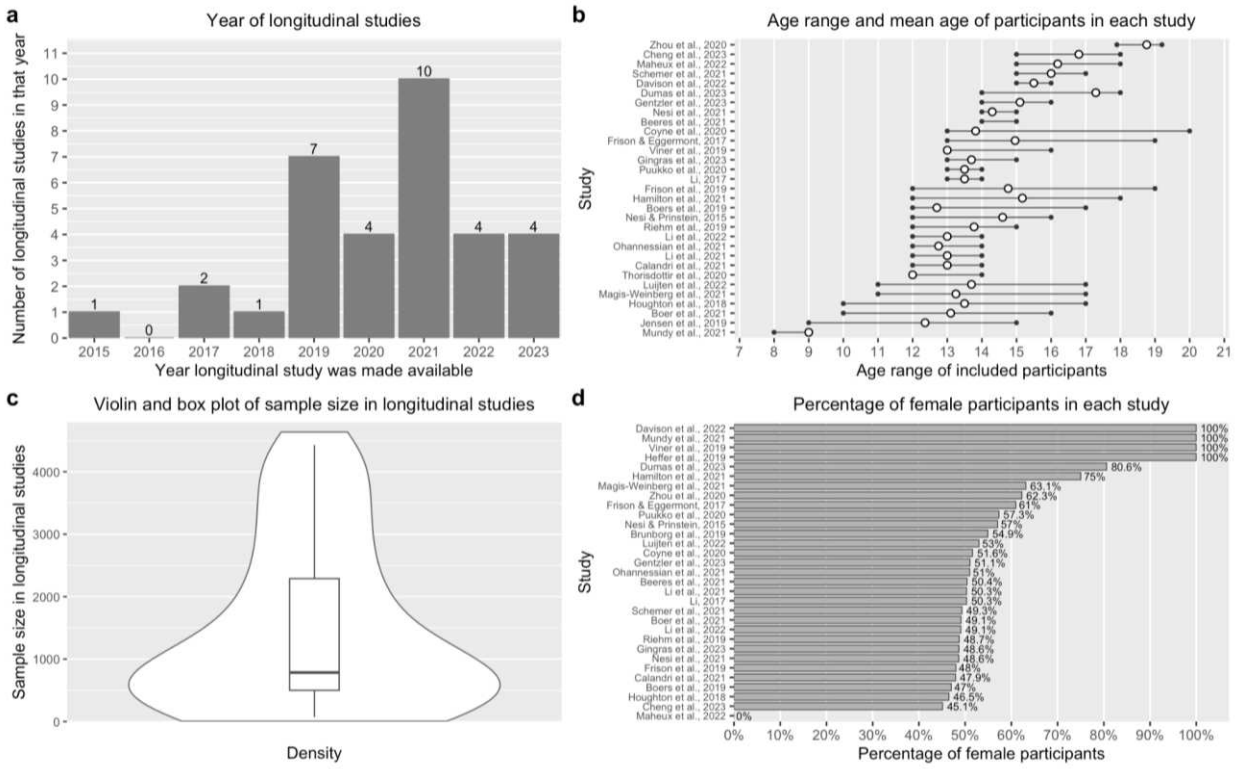


Figure 4. Characteristics of the included longitudinal studies. a, Histogram of the number of longitudinal studies published in each year. **b**, Age range and mean age of participants included in each longitudinal study. **c**, Violin and box plot of sample size in 33 longitudinal studies. **d**, Percentage of female participants in each longitudinal study.

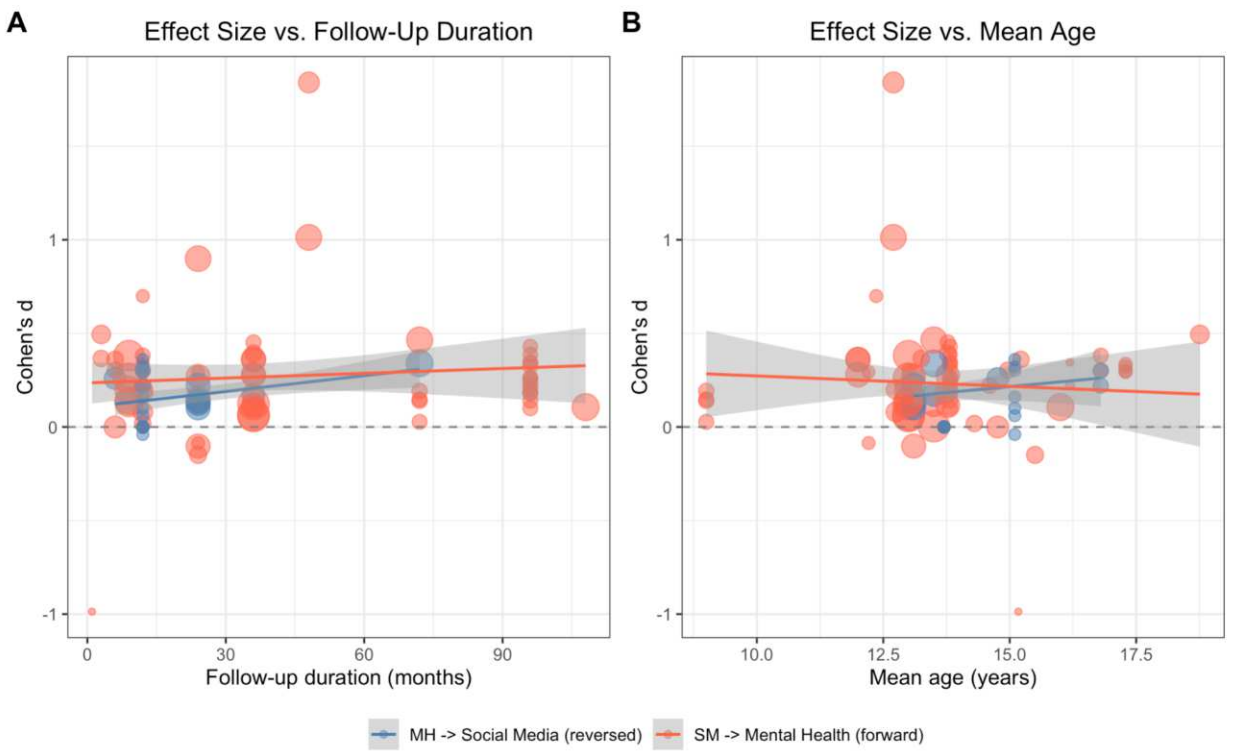


Figure 5. Bubble plot. A, Bubble plot of effect sizes and longitudinal studies' duration. **B**, Bubble plot of effect sizes and mean age.

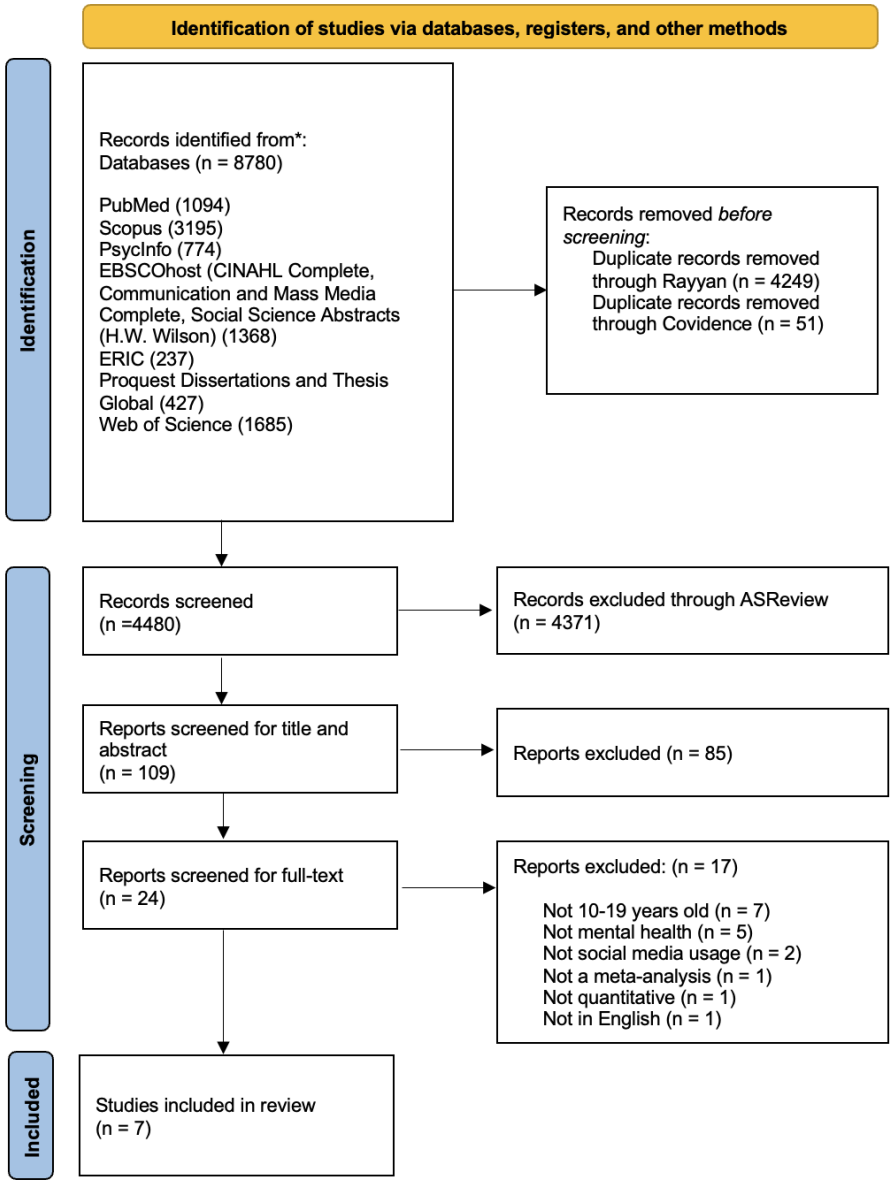


Figure 6. PRISMA flow chart.

Supplementary Files

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- Supplementarymaterials.docx