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Fear of Missing Out (FoMO) and Compulsive Social Media Use: A Systematic Review and Meta-Analysis of the Association and Moderating Effects of Age and Gender

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Correspondence regarding this article should be addressed to Kritika Bakshi & Peter Gait. Email: 8kritikabakshi@gmail.com, Petergait123@gmail.com . This research was conducted independently and was not affiliated with any institution. The authors declares no conflicts of interest. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. Grammar and language consistency were reviewed using Grammarly (Grammarly Inc., 2026). All data, materials, and analysis scripts are openly archived on OSF (https://osf.io/z42xe/).

ABSTRACT

Despite a growing literature linking Fear of Missing Out (FoMO) to compulsive social media use, the magnitude of this association across diverse populations, its demographic boundary conditions, and its theoretical mechanisms remain inadequately quantified. This pre-registered systematic review and random-effects meta-analysis (PROSPERO CRD420261322847) quantified the FoMO–problematic social media use (PSMU) association, tested age and gender as theoretically motivated moderators, and applied Prospect Theory and loss aversion as an organising theoretical lens.

Searches across five databases (PsycINFO, MEDLINE, Web of Science, Scopus, PubMed) and supplementary sources identified 19 eligible cross-sectional studies (N = 10,781) from nine countries across four continents (2022–2026). All studies operationalised FoMO using the validated 10-item Fear of Missing Out Scale; 79% used the Bergen Social Media Addiction Scale.

The pooled association was large and significant: $r = .49$, 95% CI [.44, .54], $z = 20.69$, $p < .001$, $I^2 = 90.84\%$ (REML). The 95% prediction interval (r [.30, .68]) confirmed that a large positive association is expected even in the least favourable comparable population. The estimate was stable across all six pre-specified sensitivity analyses. Geographic region did not moderate the association. COVID-19 data collection context emerged as the most consequential exploratory moderator ($R^2 = 60.62\%$), with the single pandemic-era study producing $r = .75$ versus a non-COVID pooled estimate of $r = .47$ directionally consistent with loss-aversion amplification under elevated social disconnection costs. Pre-registered age (H2) and gender (H3) moderation were not supported; both null results are constrained by

statistical power (k = 19), and the gender null additionally reflects the ecological invalidity of between-study gender composition as a proxy for individual-level relational self-construal hypotheses. Publication bias evidence was weak across six convergent methods.

FoMO is a large predictor of compulsive social media use, observed consistently across nine countries and four continents. Prospect Theory provides a parsimonious account of both the consistency and context-sensitivity of this association, with implications for FoMO-targeted clinical screening, cognitive-behavioural intervention, and regulatory evaluation of platform design features that exploit loss-aversion-driven social monitoring.

Keywords: fear of missing out, problematic social media use, social media addiction, meta-analysis, systematic review, loss aversion, Prospect Theory.

1.Introduction

1.1 Social Media and Excessive Use

It is difficult to exaggerate the magnitude of social media use today as over 5.2 billion people use these platforms daily (Data Report, 2024). What remains genuinely contested, however, its impact on psychological health.There is reasonable evidence that social networking supports connection and subjective wellbeing, but there is an equally substantial and growing literature documenting patterns of use that are compulsive, poorly controlled, and associated with real psychological harm. Social networking sites have become the primary space where social life takes place: a place to stay connected, express identity, find peer support, and access information (Godard & Holtzman, 2024; Kuss & Griffiths, 2011; Naslund et al., 2020), especially for adolescents and young adults. But the research doesn't paint a picture of everything being hunky-dory. Active and communicative use of online platforms can improve wellbeing and social ties, but when it turns into comparison and compulsive use, the

associations with psychological outcomes are consistently negative (Marciano et al., 2024). This latter pattern of excessive use, which is difficult to regulate and which disrupts daily life and mental health, has received increasing scholarly attention (Huang, 2022; Shannon et al., 2022). Research output in this area has increased sharply in the past decade (Pellegrino et al., 2022) and cross-national work has confirmed that problematic patterns of use are not culturally specific, although reported prevalence varies greatly according to the definitions and instruments applied (Cheng et al., 2021).

What constitutes problematic social media use needs to be carefully defined. PSMU is defined by excessive, poorly regulated use of social networking platforms that persists despite the costs to the individual. It is not, to be clear, a synonym for frequent use. Many people use social media heavily and function well; what distinguishes PSMU is the presence of impaired control persistent preoccupation with platforms, difficulty stepping away, and continued engagement despite emotional distress, interpersonal damage, or academic and occupational disruption (Andreassen & Pallesen, 2014; Casale, 2020; Kuss & Griffiths, 2011). High usage without these features does not constitute PSMU, and conflating the two risks pathologising normal behaviour. Three instruments dominate the measurement landscape: the Bergen Facebook Addiction Scale (Andreassen et al., 2012), the Bergen Social Media Addiction Scale (Andreassen et al., 2017), and the Social Media Disorder Scale (van den Eijnden et al., 2016). All three operationalise PSMU through symptom clusters salience, withdrawal-like states, tolerance, mood modification, conflict, and relapse drawn from behavioural addiction models. Importantly, these tools are not measuring the same thing in the same way: addiction-framework scales such as the BSMAS and BFAS approach PSMU differently from disorder-based instruments like the SMDS, and there is meaningful evidence that this distinction affects obtained effect sizes and contributes to the heterogeneity observed across studies (Casale, 2020; Fournier et al., 2023). The clinical relevance of PSMU as a

construct has, nonetheless, been substantiated repeatedly in systematic reviews and meta-analyses, which find associations with elevated depression, anxiety, stress, and diminished wellbeing particularly, though not exclusively, among younger populations (Huang, 2022; Shannon et al., 2022).

PSMU has not been accorded formal diagnostic status in either the DSM-5-TR or the ICD-11. Gambling disorder sits within the DSM-5-TR as a recognised behavioural addiction; gaming disorder appears in the ICD-11; PSMU does not feature in either system, at least not yet (American Psychiatric Association, 2022; Brand et al., 2022; World Health Organization, 2022). This absence does not, however, prevent meaningful theoretical analysis. Griffiths' (2005) components model remains the most widely applied framework, proposing that any behavioural addiction can be characterised by six components: salience, mood modification, tolerance, withdrawal, conflict, and relapse. These include: preoccupation with the social media platform, using social media to manage or escape from feelings, increased use over time, feelings of discomfort or irritability when access is denied, conflict with responsibilities and relationships, and unsuccessful attempts to cut down use. The analytical value of this framework is that it reorients the question away from how many hours someone spends online and towards whether control over engagement is actually intact, and whether that engagement is causing genuine harm (Andreassen et al., 2017; Griffiths, 2005; Kuss & Griffiths, 2011).Since then, Peng and Liao (2023) have investigated the association of these specific components of addiction with depression, anxiety, and stress in populations with PSMU. The addiction frame is not without its critics, however. There is a legitimate concern that use of addiction language in social media risks over medicalising what may be simply enthusiastic but functional use, and that it obscures the more meaningful distinction between distress, impaired control and interference with daily life on the one hand, and intensity of use on the other (Fournier et al., 2023).

1.2 Fear of Missing Out (FoMO)

Fear of Missing Out FoMO describes a pervasive apprehensiveness that other people are having experiences you are not part of, combined with a compulsive drive to stay informed about what others are doing (Przybylski et al., 2013). The concept predates social media; people have always worried about being left out. Digital platforms have added a new and persistent form of that anxiety. Social media reveals potential exclusion in a way that has no real historical precedent, because it provides a near-constant feed of updates about others' social lives, relationships, achievements, and experiences. For those who suffer from FoMO, this stream of information is not a pleasurable browse but rather a monitoring task, driven by the desire to remain socially aware and to avoid the discomfort of disconnection (Gupta & Sharma, 2021; Roberts & David, 2019; Wegmann et al., 2017).

The theoretical basis of FoMO is mainly grounded in the Self-Determination Theory, which posits that the psychological wellbeing is dependent on the fulfilment of three basic psychological needs - autonomy, competence, and relatedness (Ryan & Deci, 2000).Przybylski et al(2013) interpreted FoMO as a response to a lack of relatedness, where the failure to satisfy the need for social connection informs people of the prospect of further exclusion or lost belongingness. From this perspective, FoMO is not so much a personality trait as an emotional cue that something important is missing. Consequently, persons who are chronically under-connected may experience heightened anxiety around the potential exclusion from socially gratifying activities, prompting them to utilise social media as a compensatory avenue for social information and a sense of belonging (Elhai et al., 2016; Gupta & Sharma, 2021). This phenomenon has been recognized in recent studies as being defined by compulsive checking behaviour, heightened social surveillance, and uninterrupted

online activity to reduce uncertainty and to maintain a sense of social presence (Elhai et al., 2016; Topino et al., 2023; Wegmann et al., 2017). FoMO is directly relevant to any framework trying to shed light on the compulsive traits of social media usage in relation to certain behavioural patterns.

1.3 Social media addiction and FoMO

Consistently, the positive relationship between FoMO and PSMU has been identified; however, the degree of the strength of the relationship between the two variables has not been sufficiently quantified. Pursuing higher levels of FoMO has been associated with PSMU characteristics such as habitual checking, over engagement to platforms, difficulty in pulling away, and lower self-regulation over use in adolescent, student, and adult samples (Błachnio & Przepiorka, 2018; Elhai et al., 2016; Servidio et al., 2024; Wang et al., 2019). This finding has been consistently replicated across cultures, types of samples, and measurement instruments (see reviews and meta-analyses; Fioravanti et al., 2021; Jing et al., 2025). Also, there is increasing evidence that the causal story may not be one-way compulsive social media use may increase FoMO in turn, creating a feedback loop that sustains both (David & Roberts, 2023).

An integrated mechanistic account of this association centres on a self-reinforcing cycle: FoMO is associated with threat-monitoring behaviours, temporary relief from checking reinforces future engagement, and the ongoing salience of the activities of others maintains the original state of FoMO a cycle consistent with both models of behavioural addiction and the principle of loss aversion considered in the next section. Checking a platform might be a temporary relief for the anxiety of exclusion, but the relief is only for a short time, the flow of information continues and so does the monitoring (Elhai et al., 2016; Topino et al., 2023; Wegmann et al., 2017). There is also an additional layer of emotional dysregulation: high FoMO individuals who have difficulty regulating negative affect may engage with social

media as a coping strategy, even though it may further worsen the problem (Flack et al., 2024; Gori et al., 2024). This aligns with predictions from behavioural addiction models, where compulsive behaviours are often perpetuated as they bring about temporary relief from psychological distress rather than sustained relief (Brand et al., 2022; Griffiths, 2005).This fixated use is not only due to the allure of societal benefits, but also a desire to avoid the discomfort of feeling excluded, misinformed, or socially marginal (Benzi et al., 2024).

FoMO and PSMU have an inconsistent relationship. The correlation seems to be worsened by reduced self-esteem, increased neuroticism, depressive symptoms, lack of emotional control and interpersonal insecurity (Benzi et al., 2024; Gori et al., 2024; Packer & Flack, 2024). Adolescents and emerging adults are particularly vulnerable: the developmental demands of this period (e.g., establishing peer acceptance, social status, and identity) increase the salience of social belonging, while the regulatory capacities that buffer against these demands have not yet developed (Barry et al., 2017; Oberst et al., 2017). Another complication of the COVID-19 pandemic is that the face-to-face encounters have decreased and digital communication has become more and more important in social life, perhaps increasing the perceived costs of being ignorant (Cauberghe et al., 2021; Zhao & Zhou, 2020). Such patterns do exist, but estimates of the size of the impact vary widely across studies, and it is not clear how much of this variation is due to demographic and individual-level factors.

A lot of the inconsistency is methodological. Most of the literature is based on cross-sectional designs, which do not permit the separation of cause and effect or the test of bidirectional dynamics that some researchers are beginning to put forward (David & Roberts, 2023). Longitudinal evidence is scant. The sampling base is also narrow student and young adult populations feature disproportionately, which raises legitimate questions about how broadly existing conclusions apply (Kuss & Griffiths, 2011; Servidio et al., 2024; Shannon et al.,

2022). Taken together, these limitations produce the kind of between-study variability that warrants quantitative synthesis rather than narrative accumulation.

1.4 Prospect Theory and Loss Aversion as a Theoretical Lens

Existing accounts of FoMO have drawn primarily on motivational, social comparison, and behavioural addiction frameworks. Each captures something real, but none fully explains one of the most striking features of the phenomenon: why the drive to check feels so urgent, so difficult to resist, even when people are aware it is not helping them. Prospect Theory offers an answer. Kahneman and Tversky's (1979) foundational work established that people evaluate outcomes not against an absolute standard but relative to a reference point, and that the psychological weight of a potential loss is substantially greater than the equivalent gain what they termed loss aversion (Tversky & Kahneman, 1991). This asymmetry, where losses feel more pressing than gains feel appealing, predicts that behaviours aimed at avoiding loss will be more strongly motivated, more persistent, and more resistant to inhibition than those aimed at obtaining reward.

This is an extension of SDT-based accounts, not a replacement for them. SDT identifies the motivational origin: FoMO arises when relatedness needs go unsatisfied. Prospect Theory identifies why the response to that unmet need takes the form it does. When social connection is the reference point, any indication that others are having experiences you are missing becomes a potential loss signal and loss signals, under loss aversion, compel action more forcefully than equivalent gain signals would. A notification about a gathering you were not invited to, a photograph of friends you were not with, an update about an event you did not attend each registers as evidence of social loss, and the impulse to check becomes an impulse to prevent that loss from accumulating. The relief offered by checking is not about gaining information; it is about temporarily reducing the aversive experience of anticipated loss. This

interpretation fits well with previous evidence associating FoMO with negative affectivity, online engagement, and problematic technology use, as well as findings that FoMO promotes continued platform use as a form of distress regulation (Elhai et al., 2018; Elhai et al., 2021).

Prospect Theory also helps make sense of the wide variability in FoMO–PSMU effect sizes across studies. If loss aversion is partly driving the association, then its strength should depend on how high-stakes the relevant social reference point is for a given group in a given moment. Where social disconnection carries serious psychological cost whether because developmental vulnerability is high, or because external circumstances have disrupted normal social access the asymmetry should be greater and the association stronger. The COVID-19 pandemic was, in this respect, a natural experiment. Physical distancing removed the face-to-face contact that ordinarily anchors social life and shifted the reference point so that being online became not optional but necessary for maintaining relationships, awareness, and emotional support (Cheng & Lau, 2022). The anticipated cost of disconnection of missing what was happening likely became disproportionately large under these conditions, potentially strengthening loss-aversion-driven checking. Evidence from the pandemic period is consistent with this: FoMO predicted more positive orientations toward online communication during lockdown (Gioia et al., 2021), and social media use functioned increasingly as a coping mechanism for the social deprivation that isolation created, potentially amplifying loss-aversion-driven monitoring behaviour (Cauberghe et al., 2021; Zhao & Zhou, 2021). Studies conducted during this period may therefore reflect a qualitatively distinct social reference context, which is why pandemic data collection context was examined as an exploratory post-hoc moderator in the present review.

It bears stating explicitly: Prospect Theory is deployed here as an interpretive lens, not a formally tested variable. It is not measured in the included studies; it is used to organise and make sense of the patterns that emerge from them.

1.5 Theoretically Motivated Moderators

Not everyone is equally susceptible to FoMO-driven compulsive use. Age and gender were identified as the primary candidates for formal moderation testing, on theoretical grounds: both reflect meaningful differences in how social comparison, social sensitivity, and the regulation of socially driven behaviour operate across individuals and developmental periods (Andreassen et al., 2017; Blakemore & Mills, 2014; Steinberg, 2008).

The case for age as a moderator rests on what we know about adolescent and emerging adult development. These are defined by a greater sensitivity to peer evaluation, greater concern with belonging and social status, and a slower maturation of self-regulatory systems (Blakemore & Mills, 2014; Steinberg, 2008). Social media, in this context, is not simply a communication tool it is a primary site for monitoring peer activity, managing social status, and tracking inclusion and exclusion. FoMO should accordingly exert stronger influence over social media behaviour during these years, when the social stakes feel highest and the capacity to inhibit anxiety-driven checking is still developing (Barry et al., 2017; Oberst et al., 2017). The highest rates of problematic patterns of use are consistently found among adolescents and young adults in the PSMU research (Shannon et al., 2022). Age is therefore hypothesised to attenuate the FoMO–PSMU association: as developmental vulnerability to peer evaluation and social comparison diminishes with age, so too should the strength of the link.

Gender is more complicated. Data indicates that women are generally more socially intensive, relational, and affiliation-oriented online, and more prone to social feedback and social comparison (Andreassen et al., 2017; Shannon et al., 2022). One well worked out theoretical explanation for this is the idea of relational self-construal - the extent to which

identity is based on social bonds and interpersonal connection (Cross & Madson, 1997). In contexts where self-definition is intensely relational, perceived exclusion or social disconnection is not simply inconvenient but rather self-threatening, which should enhance the motivational pull of FoMO-driven monitoring (Meier & Reinecke, 2020). Platform features might also be relevant here.Affective responses to evaluative, visually oriented platforms are likely to be stronger for female users, as these platforms emphasize appearance and social comparison, potentially reinforcing the association between FoMO and compulsive engagement (Vogel et al., 2014). That said, gender differences are not consistent across all studies, and they interact with age, platform type, and how PSMU is operationalised in ways that narrative review alone cannot resolve (Cheng et al., 2021; Shannon et al., 2022). Whether gender reliably moderates the FoMO–PSMU association in the expected direction is therefore an empirical question this review is designed to answer.

In addition moderators included self-esteem and kind of platform. Lower self-esteem likely increases sensitivity to social comparisons and perceived rejection, encouraging FoMO-driven engagement (Servidio et al., 2024). Different platforms provide different levels and types of social comparison content for users which may affect the extent to which FoMO is exhibited as obsessive checking (Meier & Reinecke, 2020; Vogel et al., 2014). Neither variable, however, met the pre-specified threshold for formal moderation testing: fewer than five included studies provided validated self-esteem data or platform-specific information, below the minimum required for meta-regression under the registered protocol (PROSPERO CRD420261322847). Both are therefore addressed through narrative synthesis where the data permit.

Formal moderation analyses thus examine age and gender. Self-esteem and platform type are treated narratively.

2 Research Gap and Current Review

The FoMO–PSMU literature is, by now, sizeable. What it has not yet produced is a rigorous, theoretically coherent quantitative synthesis that simultaneously estimates the overall association, tests who it is strongest for, and situates the findings within an explanatory framework that accounts for both the consistency of the effect and the variability around it. Prior meta-analyses have addressed adjacent questions but have worked primarily within student samples, without systematic moderator testing capable of explaining the considerable heterogeneity in reported effect sizes (Fioravanti et al., 2021; Jing et al., 2025). That heterogeneity almost certainly reflects genuine variation in participant age, cultural setting, study quality, and the particular instruments used to capture PSMU and understanding its sources requires the kind of analysis this review undertakes (Casale, 2020; Fournier et al., 2023; Shannon et al., 2022). The field's reliance on adolescent and student samples also limits the degree to which existing conclusions can be extended to broader adult populations (Bányai et al., 2017; Kuss & Griffiths, 2011; Shannon et al., 2022).

This study addresses these limitations through a pre-registered systematic review and random-effects meta-analysis (PROSPERO CRD420261322847) that drew on peer-reviewed publications, preprints, and grey literature. The contribution is specific in three ways: first, pooled effect size estimation across adolescent, young adult, and adult populations; second, formal moderator testing for age and gender, with narrative synthesis of self-esteem and platform type where data were insufficient for meta-regression; and third, the application of Prospect Theory and loss aversion as an organising theoretical framework through which the consistency, magnitude, and heterogeneity of the FoMO–PSMU association can be interpreted. Three pre-registered hypotheses were tested. H1 predicted a significant positive association between FoMO and PSMU across studies. H2 predicted that this association

would be stronger in younger samples, where developmental vulnerability to peer evaluation and social comparison is highest and self-regulatory capacity is less fully developed. H3 predicted that gender would moderate the association, with stronger effects in more female-dominant samples; given inconsistent prior evidence, this hypothesis was treated as exploratory. Publication year was examined as a secondary moderator to assess whether effect size estimates have shifted over time.

By applying loss aversion as an organising principle, the present review offers a parsimonious account of why FoMO may drive compulsive social media engagement across demographically and culturally diverse populations and why this association may intensify under conditions that elevate the perceived cost of social disconnection.

3 Method

3.1 Protocol and Registration

This systematic review and meta-analysis was submitted to PROSPERO on 21 February 2026, prior to data extraction and analysis (CRD420261322847; registered 08 May 2026). Database searches commenced 9 February 2026; the analysis plan, eligibility criteria, and statistical approach were fully pre-specified before any effect sizes were computed, consistent with the intent of prospective registration (Stewart et al., 2012). The review was conducted and reported per PRISMA 2020 (Page et al., 2021); the completed 27-item checklist is provided as Supplementary Material. All data extraction forms, screening records, and analysis scripts are openly archived on OSF (https://osf.io/z42xe/).The manuscript was edited for grammar and language consistency using Grammarly (Grammarly Inc., 2026).
A protocol amendment (Version 2.0, May 2026) reported two pre-registered moderators that could not be formally tested. 17 of the 19 studies used platform-agnostic instruments (BSMAS/BSNAS) precluding subgroup analysis by platform type. None of the categories

reached the pre-specified minimum of $k \geq 5$. Meta-regression for self-esteem was not possible since only two studies measured self-esteem using a validated instrument (Rosenberg Self-Esteem Scale; Gori et al., 2023; Sommantico et al., 2023). Both are addressed narratively in the Discussion (see PRISMA 2020 Item 24).

3.2 Eligibility Criteria

Studies were eligible per the following PICOS criteria. Population: adolescents and adults aged ≥ 13, active social media users, from any country; clinical samples recruited primarily for a psychiatric disorder unrelated to FoMO or social media use were excluded. Exposure: FoMO operationalised using the 10-item Fear of Missing Out Scale (Przybylski et al., 2013) or a validated translation; single-item, non-validated, and structurally modified measures were excluded. Comparator: none specified. Outcome: PSMU measured using a validated, peer-reviewed, social-media-specific instrument meeting behavioural addiction criteria (e.g., BSMAS, SMDS, SMAS, SNSAS); general internet use scales and IAT-derived measures were excluded. Study design: peer-reviewed cross-sectional or longitudinal survey studies reporting a bivariate Pearson r between FoMO and PSMU, or sufficient statistics to compute one; studies reporting only β, odds ratios, Spearman ρ, or SEM path coefficients without an accompanying were excluded. A minimum of $k \geq 5$ studies was required for pooling; age subgroups with $k < 5$ are reported descriptively only and excluded from formal inference. The search covered 1 January 2013 to 22 February 2026; only English-language publications were eligible, consistent with the PROSPERO language restriction (CRD420261322847).

2.3 Information Sources and Search Strategy

Searches were conducted between 9–22 February 2026 across five databases: PsycINFO, MEDLINE, Web of Science Core Collection (Science Citation Index; Social Science Citation Index), Scopus, and PubMed, consistent with the databases pre-specified in PROSPERO.

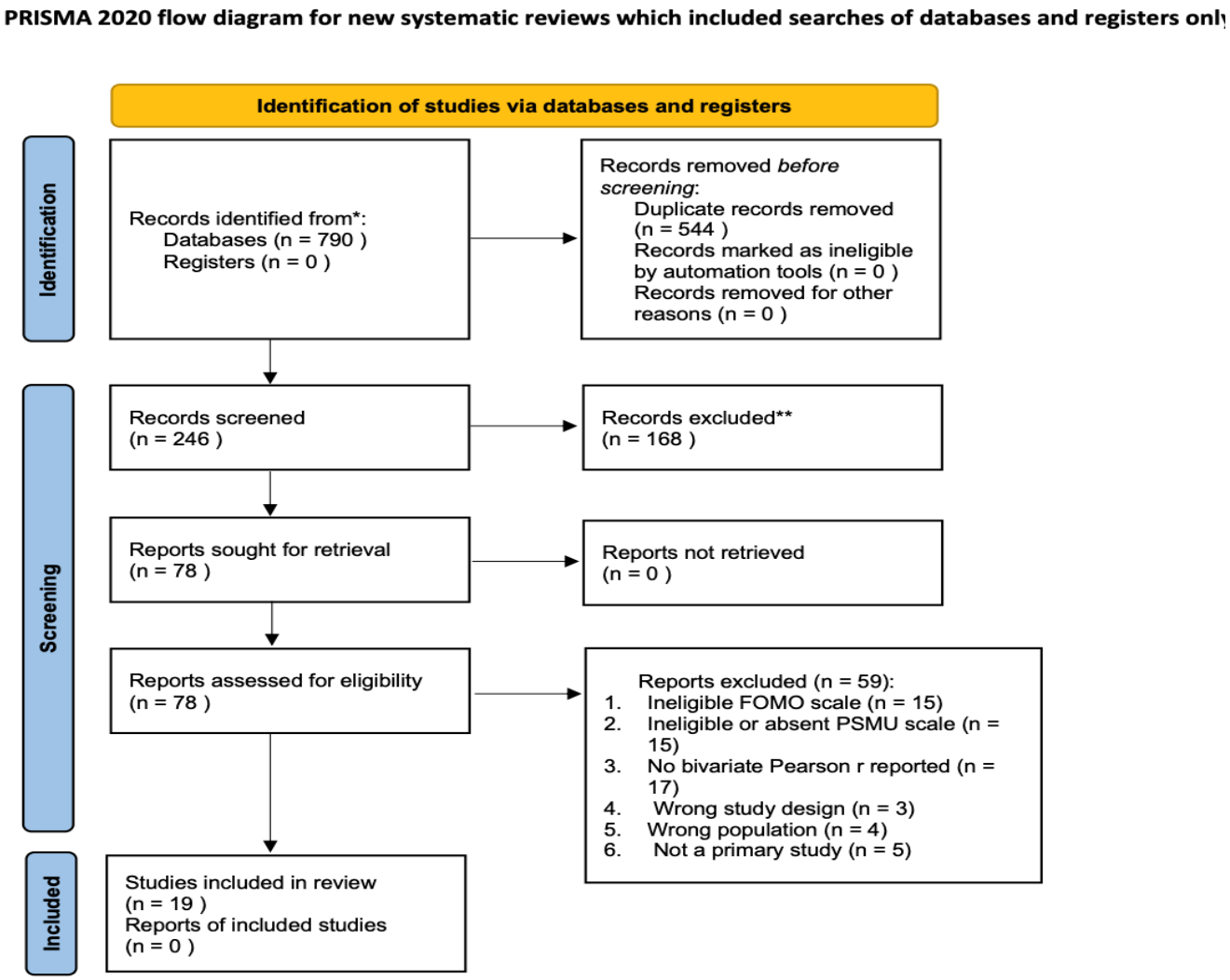
Google Scholar, Semantic Scholar, PsyArXiv, and OSF Preprints were searched supplementarily, consistent with the pre-registered supplementary search specification. The Boolean string applied across all databases was: ("fear of missing out" OR "FoMO") AND ("social media" OR "social networking" OR "social network sites") AND ("problematic use" OR "compulsive use" OR "addiction" OR "excessive use" OR "addictive use"). Six key journals were hand-searched issue-by-issue from January 2013 to February 2026: Computers in Human Behaviour, Cyberpsychology, Behaviour and Social Networking, Addictive Behaviours, Journal of Behavioural Addictions, and Behaviour & Information Technology. Forward citation searching of Przybylski et al. (2013) and backward citation searching of all included studies were conducted. Full texts were retrieved via Unpaywall (Piwowar et al., 2018) and institutional access. The complete search strategy is reported in Supplementary Table S1 and archived on OSF (https://osf.io/z42xe/).

3.4 Study Selection

Records were imported into Zotero for deduplication, reducing 790 identified records to 246. Following a pilot screen of 50 randomly selected records conducted prior to formal screening to test and refine eligibility operationalisation, consistent with the pre-registered screening procedure (PROSPERO CRD420261322847) all 246 deduplicated records were screened at title/abstract by a single reviewer using Rayyan AI (Ouzzani et al., 2016). Of these, 168 were excluded and 78 full texts were retrieved; all were successfully obtained via Unpaywall or institutional access, and no author contact was required. Following full-text review, 59 were excluded: ineligible FoMO scale (k = 15), ineligible PSMU scale (k = 15), no bivariate r (k = 17), wrong design (k = 3), wrong population (k = 4), not a primary study (k = 5). Nineteen studies were retained for synthesis (N = 10,781). Single-reviewer screening is acknowledged as a limitation, pre-disclosed in the PROSPERO protocol. The selection process is illustrated in Figure 1 (PRISMA 2020).

Figure 1.

PRISMA 2020 Flow Diagram of Study Selection



Note. Flow diagram illustrating the identification, screening, and inclusion of studies. Records were identified through database searching (n = 790) and deduplicated (n = 246). Following title/abstract screening, 78 full texts were assessed for eligibility; 59 were excluded (ineligible FoMO scale, k = 15; ineligible PSMU scale, k = 15; no bivariate r, k = 17; wrong design, k = 3; wrong population, k = 4; not a primary study, k = 5). Nineteen studies were included in the meta-analytic synthesis (N = 10,781). Adapted from Page et al. (2021).

3.5 Data Extraction

Data were extracted from all 19 studies by a single reviewer using a pre-specified form (OSF: https://osf.io/z42xe/). Variables extracted included: author(s), year, country, N, mean age (M, SD), percentage female, FoMO and PSMU scale names and item counts, Cronbach's α (extracted for all studies) and McDonald's ω (extracted where reported), Pearson r and p-value, sample type, and COVID-19 data collection context (coded dichotomously; window defined as March 2020–December 2021, reflecting the period of active national lockdowns across represented countries). All r values were extracted directly; no conversions from β, t, F, or d were performed.

3.6 Quality Assessment

All studies were appraised using the JBI Critical Appraisal Checklist for Analytical Cross-Sectional Studies (Moola et al., 2020), scored dichotomously across eight items (maximum = 8). Studies scoring below 6 were designated lower quality and examined in a pre-specified sensitivity analysis. JBI score was additionally tested as a continuous meta-regression moderator (PROSPERO Additional Outcome 5). Assessment was conducted by a single reviewer, acknowledged as a limitation. The overall certainty of the body of evidence was informally evaluated across the GRADE domains of risk of bias, inconsistency, indirectness, and imprecision and is summarised in the Discussion (Guyatt et al., 2011).

3.7 Statistical Analysis

A random-effects model with REML estimation was fitted as the primary analysis. REML was preferred over DerSimonian–Laird because simulation evidence demonstrates DL underestimates τ^2 under substantial heterogeneity (Veroniki et al., 2016), anticipated a prior given the diversity of samples, cultures, and PSMU instruments. Pearson r values were transformed to Fisher's z prior to pooling and back-transformed for reporting (Borenstein et al., 2021). Effect sizes were interpreted throughout in both Methods and Results using Gignac

and Szodorai's (2016) benchmarks for individual-differences research: small (r = .10), medium (r= .20), large (r = .30). A 95% prediction interval was computed for each pooled estimate.

A three-level model was fitted as a supplementary robustness check, nesting effect sizes within 16 independent research groups to address potential dependency across the three Servidio et al. (2022, 2025, 2026) studies. The two-level model remains primary throughout; the three-level estimate is reported alongside it. Heterogeneity was indexed by Cochran's Q ($p < .10$), I^2 (low ≥ 25%, moderate ≥ 50%, high ≥ 75%; Higgins et al., 2003), and τ^2, each with 95% confidence intervals (Ioannidis et al., 2007).

Four pre-registered moderators were examined: mean age (continuous meta-regression), age group (adolescents 13–17 vs. young adults 18–25 vs. adults 26+; subgroup analysis), gender (% female; continuous meta-regression), and publication year (continuous meta-regression). Two post-hoc exploratory moderators were added following extraction: COVID-19 context and country (Italy vs. non-Italy). Pre-registered and exploratory analyses are explicitly distinguished throughout. A minimum of $k \geq 5$ per subgroup was required for formal inference; subgroups with $k < 5$ are reported descriptively only.

Publication bias was assessed using five pre-registered methods (PROSPERO CRD420261322847): funnel plot inspection, Egger's regression test ($p < .10$; Egger et al., 1997), Begg's rank correlation test (Begg & Mazumdar, 1994), and Duval and Tweedie's (2000) trim-and-fill. PET and PEESE (Stanley & Doucouliagos, 2014) were applied as exploratory, non-pre-registered supplements.

Six sensitivity analyses evaluated robustness: leave-one-out; exclusion of Zhao et al. (2022) identified as a high-leverage outlier across DFFITS, Cook's distance, externally studentised residuals, and τ^2 deletion; exclusion of Servidio et al. (2022) ($\alpha = .69$, below the pre-specified threshold of .70); joint exclusion of all three Servidio et al. studies; exclusion of JBI < 6

studies (all 19 scored ≥ 7; no change confirmed); and publication year as a continuous moderator (PROSPERO Additional Outcome 6).All analyses were performed in R 4.4.3 (R Core Team, 2024) using the metafor (Viechtbauer, 2010) and meta (Balduzzi et al., 2019) packages. All tests were two-tailed, with an alpha level of $\alpha = .05$.

4.Results

4.1 Study Characteristics and Quality Assessment

The meta-analysis included 19 studies (k = 19) and a total sample of N = 10,781 participants (see Table 2 for full study characteristics).The studies were published from 2022-2026 and were conducted in nine countries and regions from four continents, including Italy (k=8, 42%), China (k=2), Spain (k=2), Hong Kong, Morocco, Turkey, Austria, the United States and Saudi Arabia. Sample sizes ranged from N = 151 (Gugushvili et al., 2024) to N = 2,202 (Abbouyi et al., 2026). All 19 studies employed cross-sectional designs. All studies operationalised FoMO using validated translations of the 10-item Fear of Missing Out Scale (Przybylski et al., 2013). Compulsive social media use was operationalised using the Bergen Social Media Addiction Scale (BSMAS) in 15 of 19 studies (79%); the remaining four employed the Problematic Mobile Social Media Use and Addiction Questionnaire (PMSMUAQ; Zhao et al., 2022), the Bergen Social Networking Addiction Scale (BSNAS; Steinberger & Kim, 2023), the Technology Addiction Rating Scale (TARS; Salazar et al., 2025), and a Problematic Social Media Use Scale (Al-Abyadh, 2025). Study-level correlations ranged from r = .35 (Abbouyi et al., 2026; Servidio et al., 2022) to r = .75 (Zhao et al., 2022), the latter collected during the COVID-19 period.

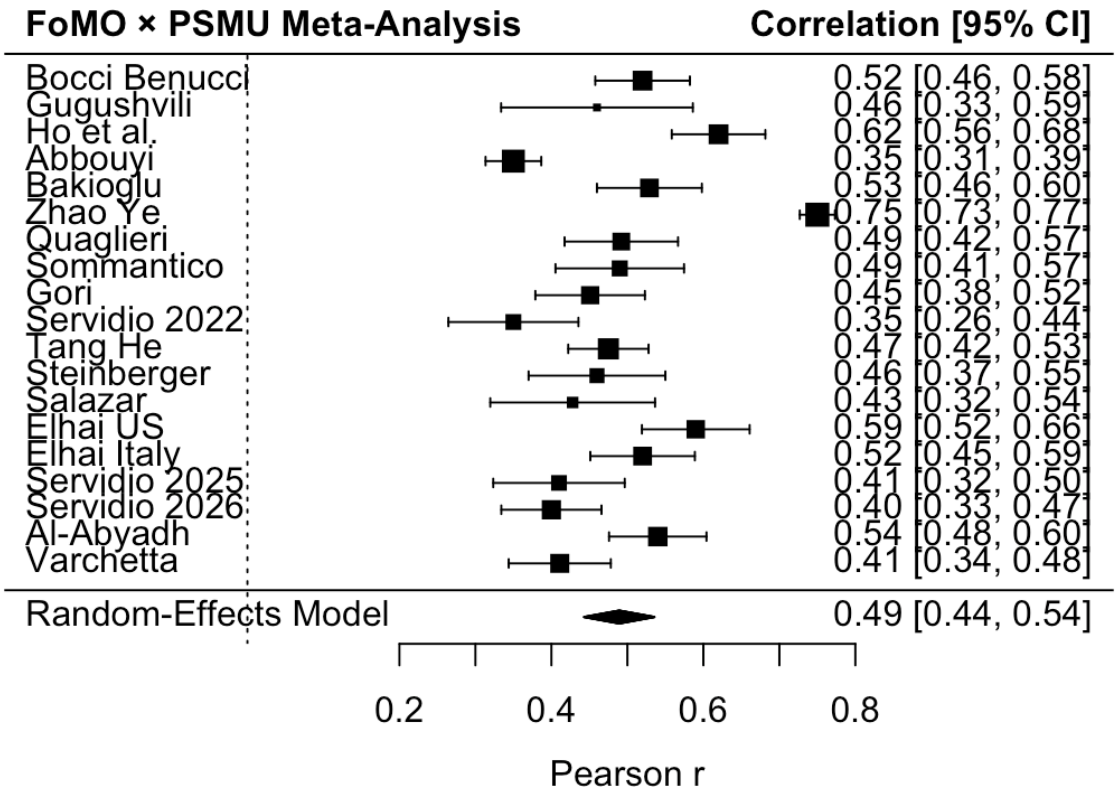
All 19 studies scored between 7 and 8 out of 8 on the JBI Critical Appraisal Checklist for Analytical Cross-Sectional Studies (mean = 7.53; range: 7–8/8). All studies satisfied criterion Q5 (confounders identified; 100%); 12 of 19 studies (63%) satisfied criterion Q6 (confounders controlled). A pre-registered meta-regression (PROSPERO Additional Outcome 5; CRD420261322847) confirmed that study quality did not significantly moderate effect size, $QM(1) = 0.06$, $p = .801$, $\beta = 0.01$, 95% CI [−0.08, 0.11], $R^2 = 0.00\%$, residual $I^2 = 91.06\%$.

Two pre-registered moderators could not be formally tested, necessitating a protocol amendment (Version 2.0, May 2026; PROSPERO CRD420261322847). Platform type could not be examined because 17 of 19 studies used platform-agnostic outcome measures (BSMAS/SMDS), with only one study employing a single-platform instrument, falling below the pre-specified threshold of k = 5 per category. Self-esteem meta-regression was not feasible because only two studies measured self-esteem using a validated instrument the Rosenberg Self-Esteem Scale (Gori et al., 2023; Sommantico et al., 2023; k = 2) below the pre-specified minimum of k = 5; three further studies assessed conceptually related but operationally distinct constructs (self-construal, loneliness) that could not be recoded as self-esteem equivalents. Both moderators are addressed narratively in the Discussion, in accordance with PRISMA 2020 guidelines (Page et al., 2021). Two supplementary publication bias estimators the Precision-Effect Test (PET) and Precision-Effect Estimate with Standard Error (PEESE; Stanley & Doucouliagos, 2014) were added post-hoc and are reported alongside the four pre-registered methods, as recommended by recent methodological guidance (Carter et al., 2019).

4.2 Primary Meta-Analytic Estimate

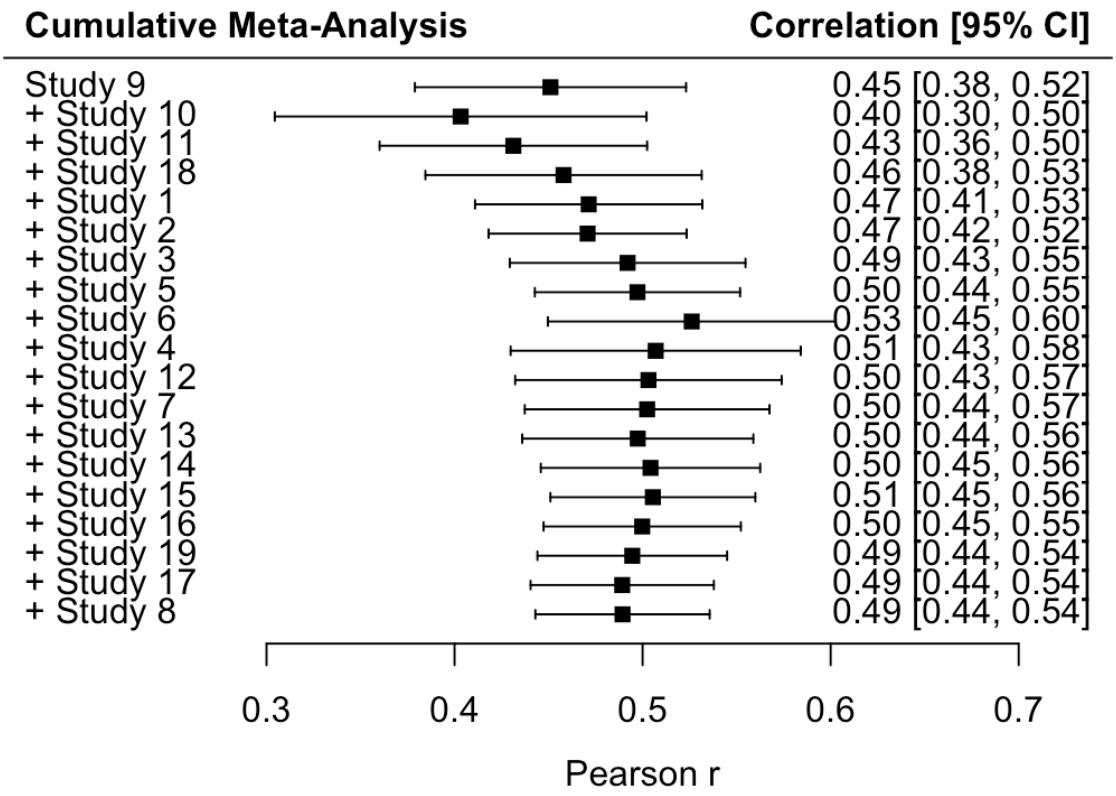
All correlations were converted to Fisher's z prior to pooling and then back-transformed to r for reporting (Borenstein et al., 2021). The random-effects model was estimated using the restricted maximum likelihood (REML) estimator since it performs better under high heterogeneity than the DerSimonian–Laird estimator (Veroniki et al., 2016). The pooled Fisher's z = 0.4893 (SE = 0.0236), z = 20.6940, p < .001, 95% CI [0.4430, 0.5357], corresponding to r = .49, 95% CI [.44, .54] (see Figure 2). The primary analysis was well-powered, with a z-statistic of 20.69 providing decisive evidence against the null across k = 19 studies. The 95% prediction interval (r [.30, .68]) indicated that in 95% of comparable populations the true effect is expected to remain positive; the lower bound (r = .30) corresponds to a large effect by individual-differences benchmarks (Gignac & Szodorai, 2016), indicating that FoMO accounted for approximately 9% of variance in compulsive social media use even in the least favourable population contexts. Temporal stability and convergence of the pooled estimate across the 2022–2026 accumulation period were confirmed by the cumulative meta-analysis (see Figure 3).

Figure 2.



Note. Forest plot of the FoMO–PSMU association across all 19 studies (random-effects, REML).

Figure 3.



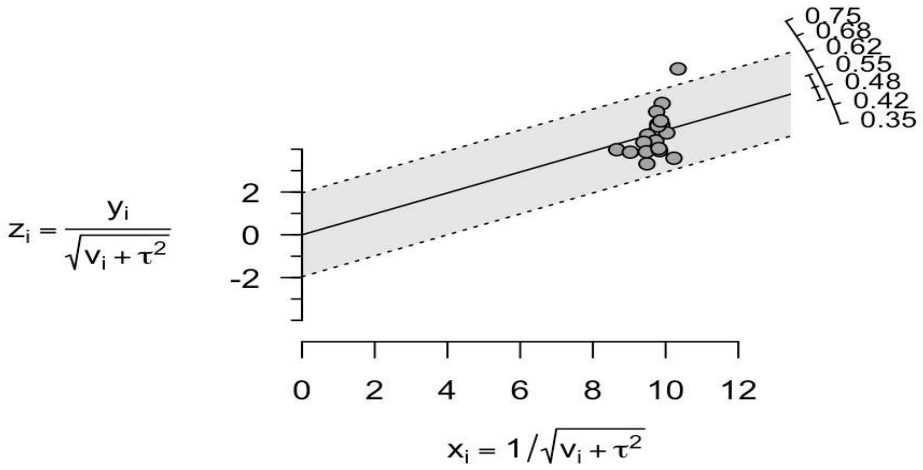
Note. Cumulative meta-analysis showing temporal stability and convergence of the pooled estimate (2022–2026)

4.3 Heterogeneity

Substantial between-study heterogeneity was observed, $Q(18) = 506.12$, $p < .001$ (significance threshold $p < .10$, as pre-specified; Higgins et al., 2003). Between-study variance was $\tau^2 = 0.0092$ (SE = 0.0035), 95% CI [0.0046, 0.0196], $\tau = 0.0960$, 95% CI [0.0676, 0.1399]; $I^2 = 90.84\%$, 95% CI [83.13%, 95.47%], consistent with the high heterogeneity threshold (Higgins et al., 2003), and motivating the moderator analyses

reported below. The Galbraith radial plot confirmed one high-leverage study (Zhao et al., 2022) deviating markedly from the pooled estimate (see Figure 4).

Figure 4.



Note. Galbraith radial plot; Zhao et al. (2022) identified as high-leverage outlier.

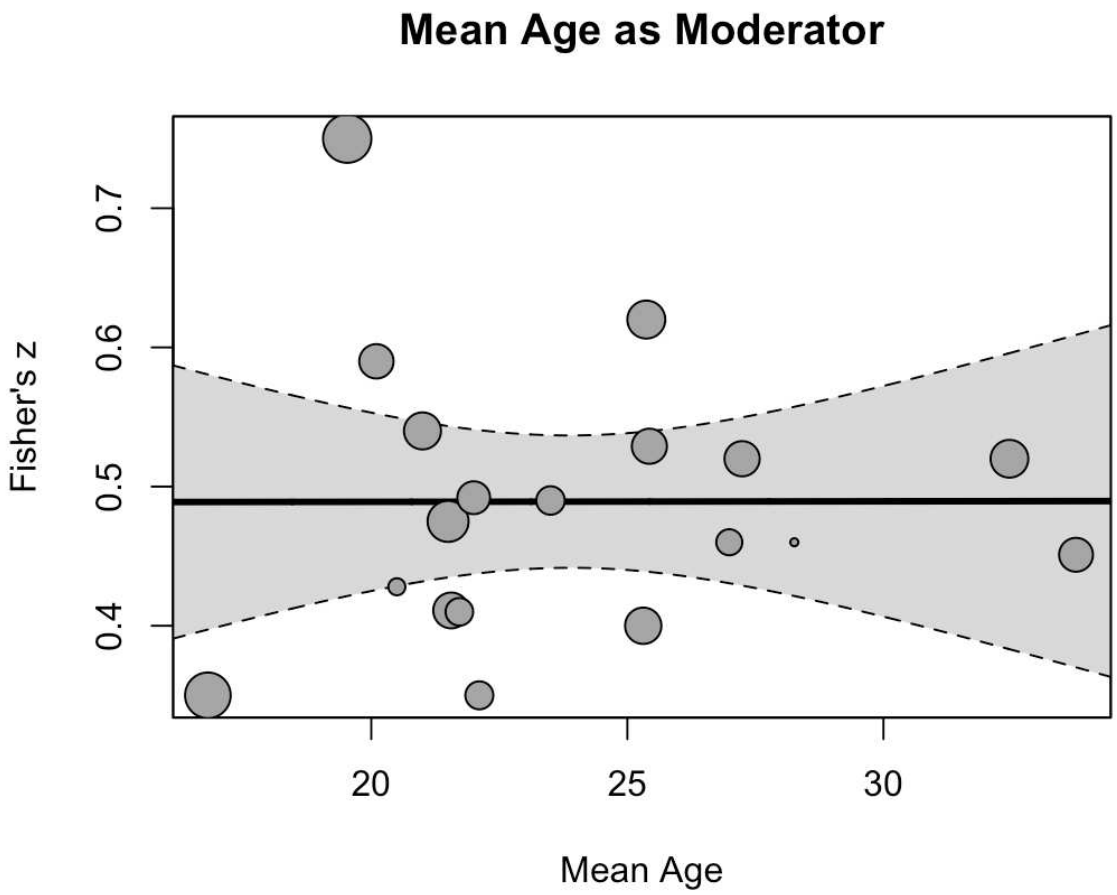
4.4 Three-Level Model

To test for reliability a three-level meta-analytic model was fit to account for potential non-independence among the three Servidio et al. studies (2022, 2025, 2026) sharing overlapping samples. Between-cluster variance was $\sigma^2_1 = 0.0093$ ($\sqrt{} = 0.0962$) and within-cluster variance $\sigma^2_2 = 0.0001$ ($\sqrt{} = 0.0078$). The three-level pooled estimate ($z = 0.4972$, $r \approx .50$, 95% CI [0.4467, 0.5476]) was virtually identical to the primary two-level result ($r = .49$), confirming that within-cluster dependency did not bias the primary estimate.

4.5 Pre-Registered Moderator Analyses

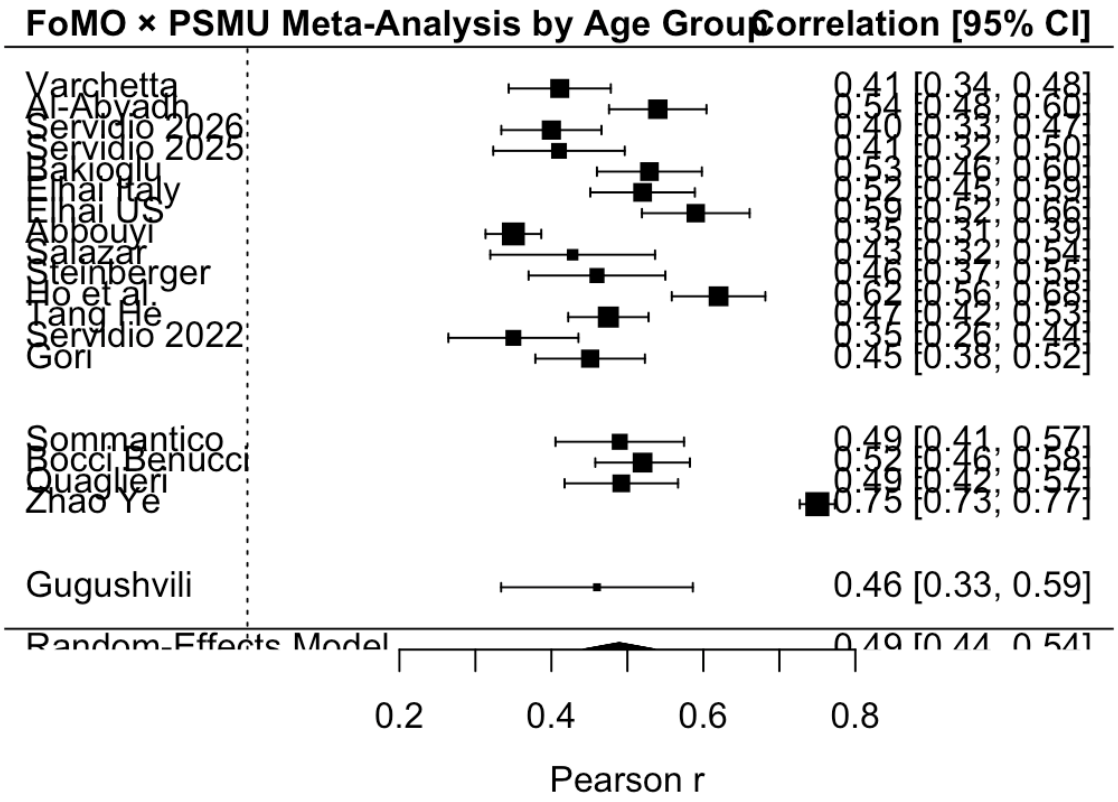
Age. Mean age as a continuous moderator did not significantly predict effect size, QM(1) = 0.0000, p = .995, b = 0.0000, SE = .0057, R^2 = 0.00% (see Figure 5). The categorical age-group omnibus test, examined using a mixed-effects subgroup model as pre-specified, was also non-significant, QM(2) = 2.2684, p = .322, R^2 = 2.97% (see Figure 6). Subgroup estimates were: r = .34, 95% CI [.30, .37] for adolescents (aged 13–17; k = 1, Abbouyi et al., 2026; this value reflects a single study's observed correlation, not a meta-analytic pooled estimate; the pre-registered objective of formally testing age-group moderation in this subgroup could not therefore be addressed); r = .46, 95% CI [.42, .51] for young adults (aged 18–25, k = 13); and r = .46, 95% CI [.43, .49] for adults (aged 26+, k = 5). The adolescent point estimate was descriptively lower than both adult subgroups, though the non-significant omnibus test precludes inferential conclusions.

Figure 5.



Note. Bubble plot: mean sample age as a continuous moderator (meta-regression).

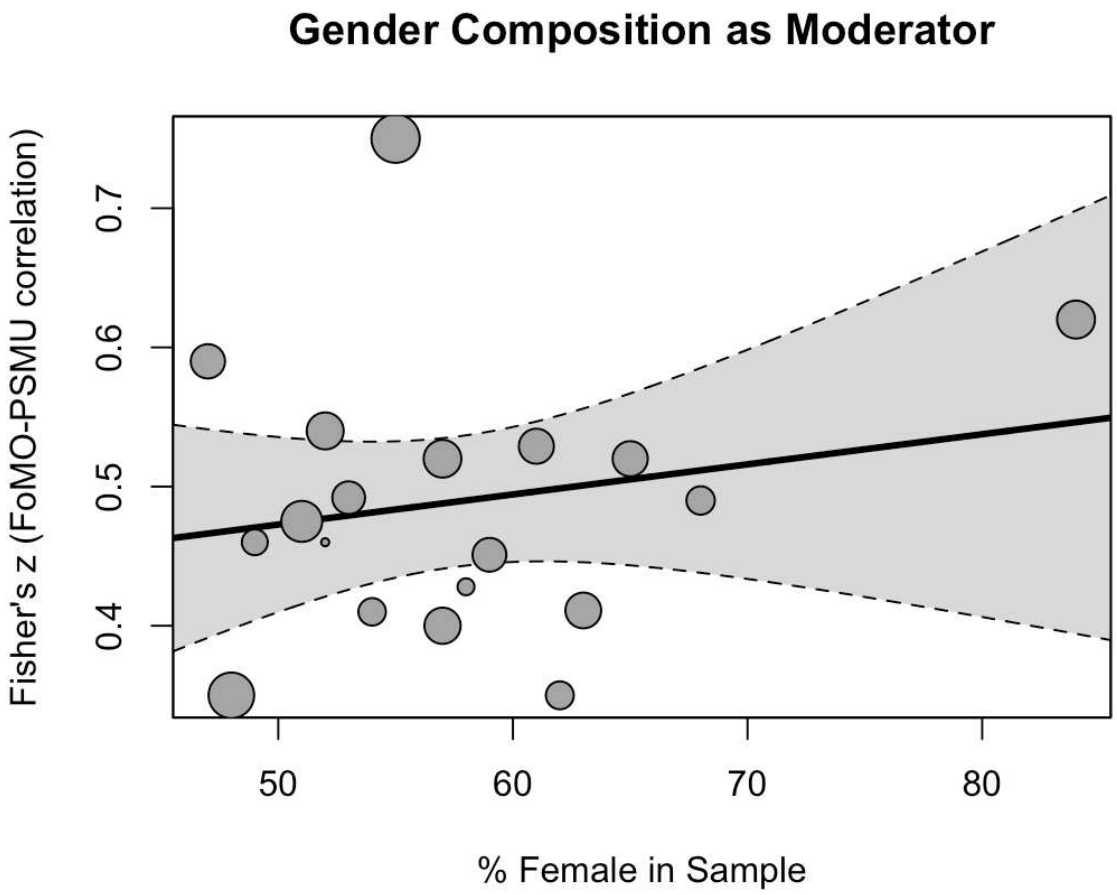
Figure 6.



Note. Mixed-effects subgroup forest plot by age group (adolescents k = 1; young adults k = 13; adults k = 5).

Gender. Proportion of female participants did not significantly moderate the association, QM(1) = 0.3551, p = .551, b = −0.0010, SE = .0016, R^2 = 0.00% (see Figure 7). Interpretation of this null result should be tempered by the limited statistical power available for moderator detection at k = 19 (Hedges & Pigott, 2004).

Figure 7.



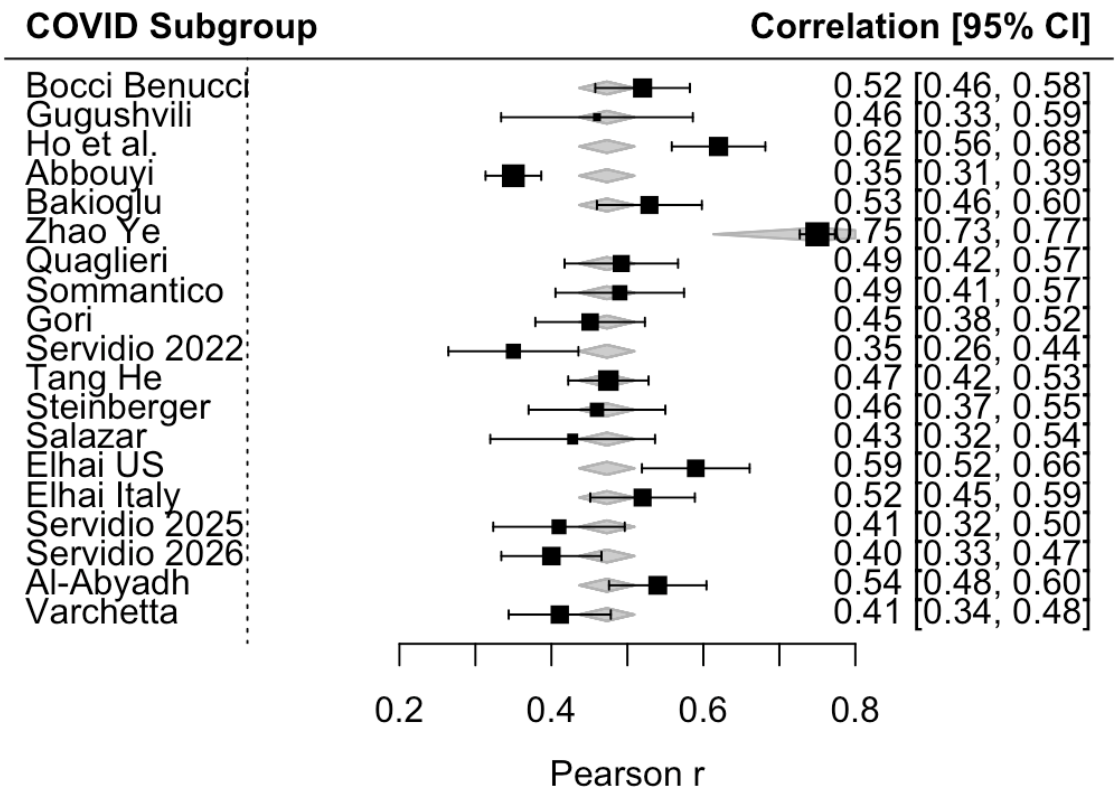
Note. Bubble plot: percentage female as a continuous moderator (meta-regression).

Publication Year. Pre-registered as Additional Outcome 6 (PROSPERO CRD420261322847), publication year did not significantly predict effect size, QM(1) = 1.4814, p = .224, R^2 = 4.79%, indicating no systematic temporal trend across the 2022–2026 publication period.

4.6 Exploratory Moderator Analyses

Three unplanned analyses were conducted post-hoc and are reported as exploratory. Studies were coded as COVID-era if data collection was documented between March 2020 and December 2021; studies with ambiguous or unreported collection periods were coded by publication year using the same window. One study met this criterion (Zhao et al., 2022; k = 1). Data collection period emerged as the most consequential moderator in the synthesis (see Figure 8): the mixed-effects subgroup model yielded QM = 23.2550, $p < .001$, $R^2 = 60.62\%$. The COVID-era study produced an observed effect of r = .75, 95% CI [.73, .77], compared with the pooled non-COVID estimate of r = .47, 95% CI [.44, .51] a difference of approximately .28 correlation units. A factor-coded model corroborated this result, QM = 14.7361, $p < .001$, $R^2 = 48.72\%$. The COVID-19 data collection period accounted for 60.62% of between-study variance, representing the largest single source of heterogeneity identified in this synthesis. Geographic region (Italy vs. non-Italy), QM(1) = 1.5703, p = .210, $R^2 = 3.86\%$, and sample type (student vs. community), QM(1) = 0.4537, p = .501, $R^2 = 0.00\%$, were both non-significant.

Figure 8.



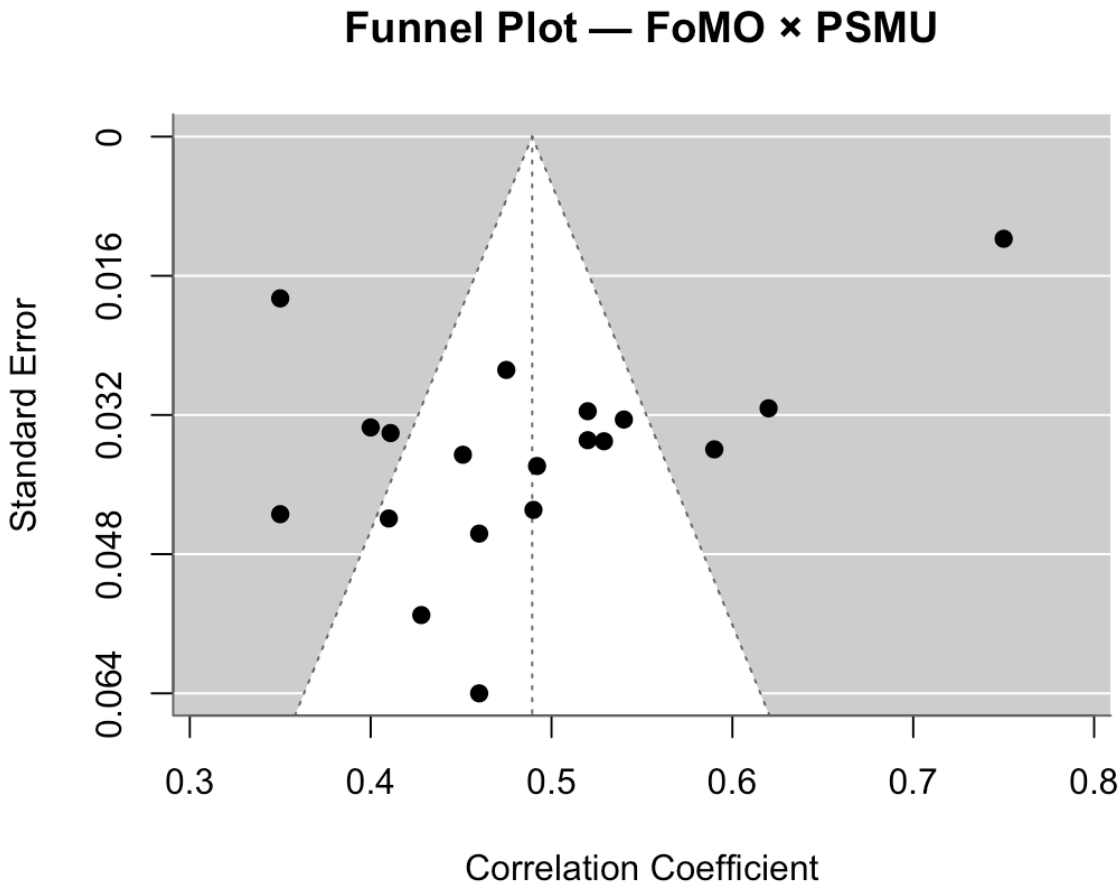
Note. Mixed-effects subgroup forest plot: COVID-19 vs. non-COVID-19 data collection period (exploratory)

4.7 Publication Bias

Six methods were employed, comprising four pre-registered and two supplementary estimators added post-hoc (PET and PEESE; see Study Characteristics and Quality Assessment). Visual inspection of the funnel plot indicated broad symmetry centred on r ≈ .49, with Zhao et al. (2022) as a clear right-tail outlier (see Figure 9). Egger's test was non-significant, z = −1.8292, p = .067; Begg's rank correlation was similarly non-significant, τ = −0.1228, p = .489. PET yielded b = 0.6202, 95% CI [.474, .767]; PEESE yielded b = 0.5457, 95% CI [.459, .633], QM p = .140. Duval and Tweedie's trim-and-fill procedure identified six

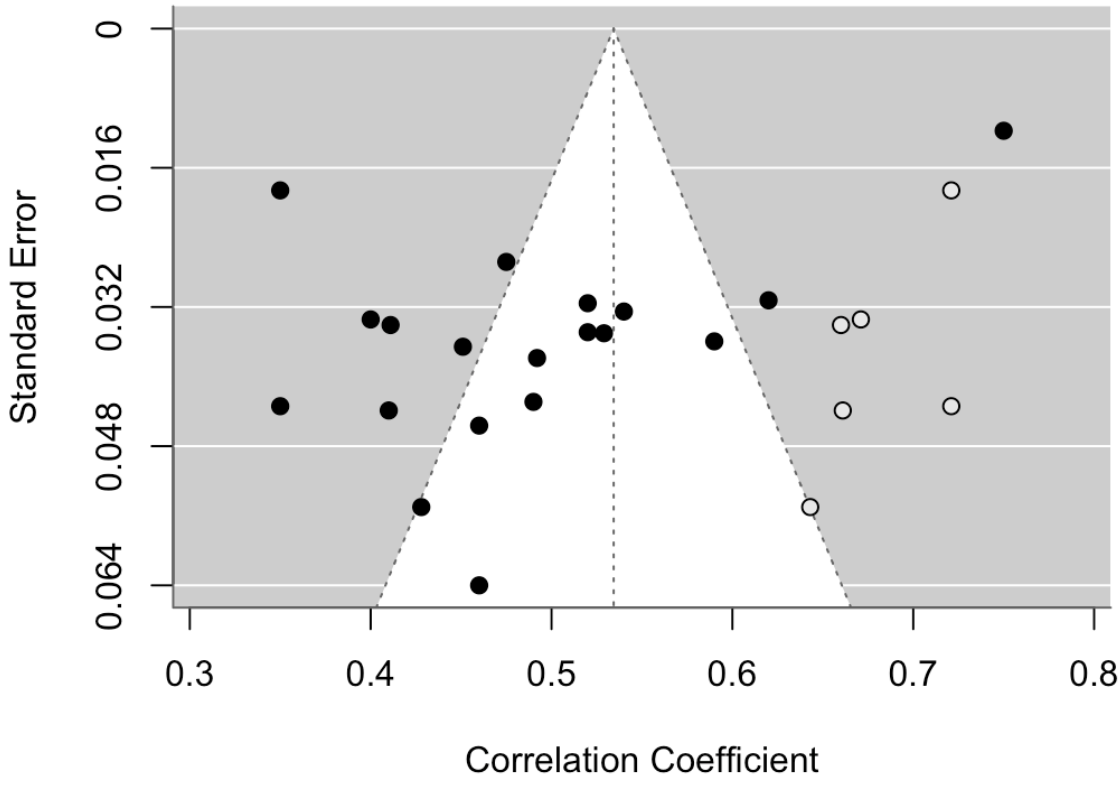
imputed studies on the right side of the funnel (see Figure 10); the adjusted estimate (r = .53, 95% CI [.49, .58]) exceeded the observed primary estimate. Right-side imputation indicates that any funnel asymmetry was not attributable to suppression of small null studies a pattern more consistent with residual heterogeneity than with conventional publication bias. Evidence for publication bias was weak and convergent across all six methods.

Figure 9.



Note. Standard funnel plot for visual assessment of small-study effects.

Figure 10.



Note. Trim-and-fill funnel plot; open circles = 6 right-side imputed studies; adjusted r = .53, 95% CI [.49, .58]

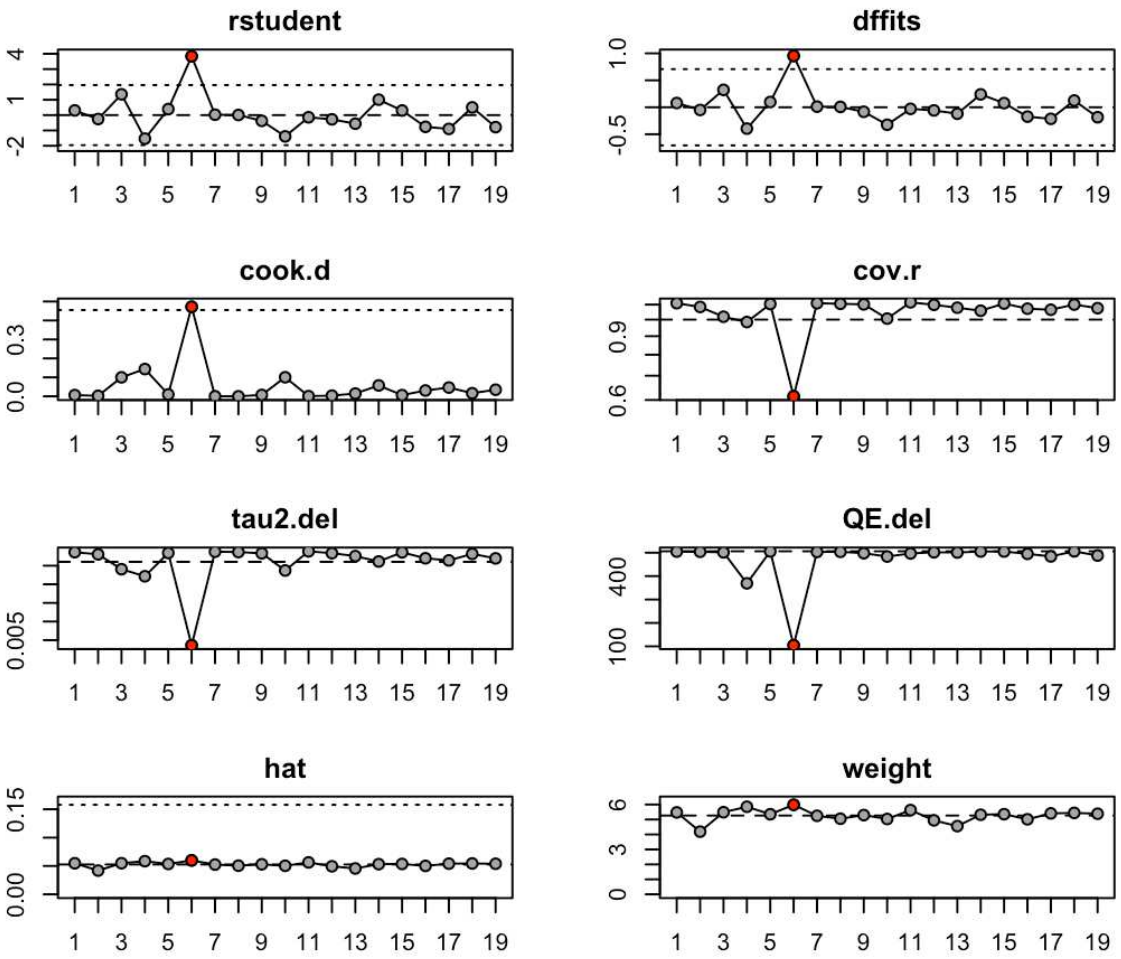
4.8 Sensitivity Analyses

The leave-one-out analysis across all 19 iterations produced pooled estimates ranging from r = .47 to r = .50, all $p < .001$, $I^2 = 79.69\%–91.53\%$, confirming that no single study drove the primary result; full leave-one-out output is archived on OSF. Three further pre-specified sensitivity analyses are reported in Table 1.

Influence diagnostics identified Zhao et al. (2022; r = .75, 95% CI [.73, .77]) the largest effect in the synthesis and the sole COVID-era study as a high-leverage outlier across externally studentised residuals, DFFITS, Cook's distance, and τ^2_{ael} (see Figure 11). Its exclusion reduced the pooled estimate to r = .47, 95% CI [.44, .51], with I^2 decreasing from 90.84% to 79.69% (k = 18; see Figure 12), identifying this study as a primary source of between-study variance. Exclusion of the low internal consistency study (Servidio et al., 2022; PSMU α = .69, below pre-specified threshold) yielded r = .50, 95% CI [.45, .54], I^2 = 90.63% (k = 18). Exclusion of all three Servidio et al. studies for potential sample overlap produced r = .50, 95% CI [.45, .55], I^2 = 90.98% (k = 17). Across all four specifications, the direction and approximate magnitude of the primary effect were preserved.

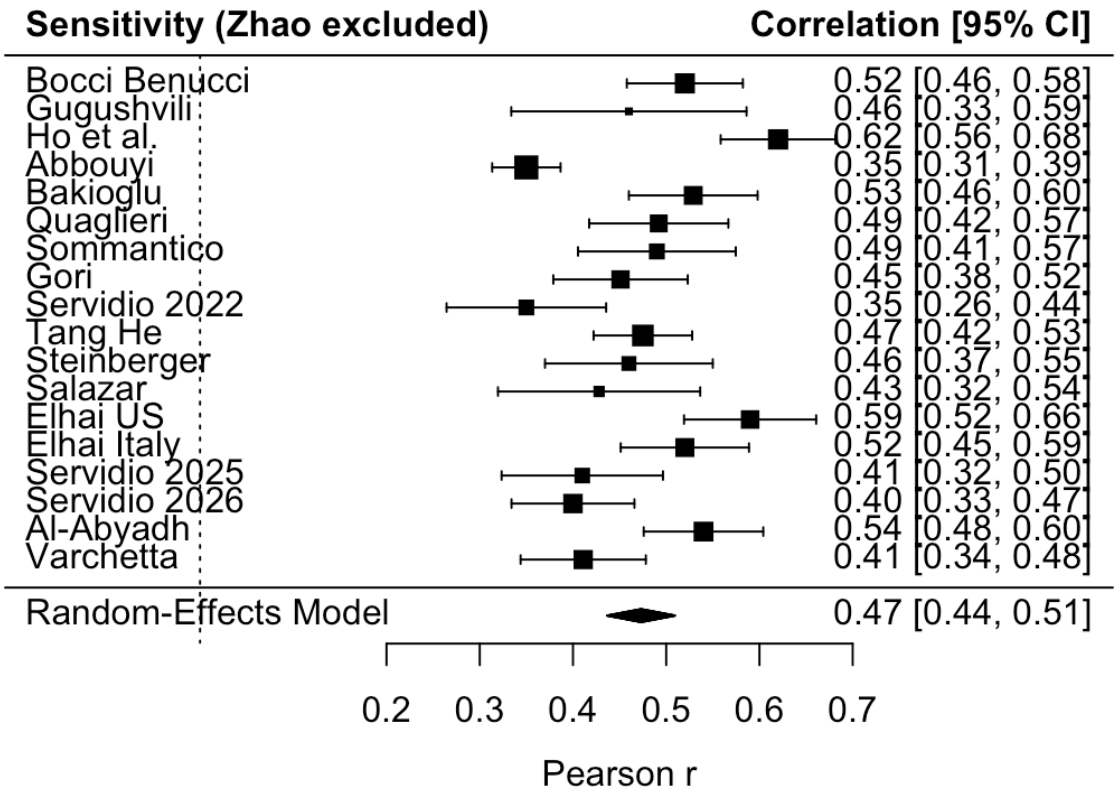
The pattern of results a medium-to-large pooled association (r = .49), high but partially explained heterogeneity (I^2 = 90.84%; COVID-era data collection period accounting for R^2 = 60.62%), and weak evidence of publication bias across six convergent methods is addressed in the context of loss aversion theory and digital wellbeing implications in the Discussion.

Figure 11.



Note. Influence diagnostics; Zhao et al. (2022) flagged across rstudent, DFFITS, Cook's d, and τ^2_{ael}

Figure 12.



Note. Sensitivity forest plot with Zhao et al. (2022) excluded (k = 18; r = .47, 95% CI [.44, .51]; I^2 = 79.69%)

Table 1

Sensitivity Analysis Results

Specification	*k*	*r*	*95% CI*	*I²*
Primary model	19	.49	[.44, .54]	90.84%
Zhao et al. (2022) excluded	18	.47	[.44, .51]	79.69%

Specification	*k*	*r*	*95% CI*	*I²*
Low-α excl. (Servidio et al., 2022)^a^	18	.50	[.45, .54]	90.63%
Servidio overlap excluded	17	.50	[.45, .55]	90.98%
Leave-one-out range	19 iter.	.47–.50	All p < .001	79.69–91.53%

Note. All models estimated using REML with random effects. I² = proportion of variance attributable to true between-study heterogeneity. CI = confidence interval.

^a^ The pre-registered sensitivity analysis specifying exclusion of studies with JBI scores below 6 (PROSPERO CRD420261322847) could not be conducted because all 19 included studies scored ≥ 7 (range: 7–8/8); the low internal consistency specification was substituted as described above.

Table 2

Characteristics of Studies Included in the Meta-Analysis (k = 19, N = 10,781)

Study	*Year*	*Country*	*N*	*r*	*FoMO Measure*	*PSMU Measure*	*FoMO α*	*PSMU α*	*COVID*	*JBI*
Bocci Benucci et al.	2024	Italy	529	.52	FoMOS (IT)	BSMAS	.85	.82	No	8
Gugushvili et al.	2024	Multi-national	151	.46	FoMOS	BSMAS	.84	.71	No	7
Ho et al.	2024	Hong Kong	385	.62	FoMOS	BSMAS	.89	.82	No	8

Study	*Year*	*Country*	*N*	*r*	*FoMO Measure*	*PSMU Measure*	*FoMO α*	*PSMU α*	*COVID*	*JBI*
Abbouyi et al.	2026	Morocco	2,202	.35	FoMOS (AR)	BSMAS	.83	.76	No	8
Bakioğlu et al.	2022	Turkey	419	.53	FoMOS (TR)	BSMAS	.81	.86	No	8
Zhao et al.	2022	China	1,373	.75	FoMOS (CH)	PMSMUAQ	.89	.89	Yes	7
Quaglieri et al.	2022	Italy	397	.49	FoMOS (IT)	BSMAS	.83	.78	No	8
Sommantico et al.	2023	Italy	311	.49	FoMOS (IT)	BSMAS	.84	.74	No	8
Gori et al.	2023	Italy	470	.45	FoMOS (IT)	BSMAS	.87	.79	No	8
Servidio et al.	2022	Italy	405	.35	FoMOS (IT)	BSMAS	.73	.69^b^	No	7
Tang & He	2025	China	825	.48	FoMOS (CH)	BSMAS	.85	NR	No	7
Steinberger & Kim	2023	Austria	296	.46	FoMOS (DE)	BSNAS	.78	.76	No	8
Salazar et al.	2025	Spain	219	.43	FoMOS (ES)	TARS	.89	.85	No	8

Study	*Year*	*Country*	*N*	*r*	*FoMO Measure*	*PSMU Measure*	*FoMO α*	*PSMU α*	*COVID*	*JBI*
Elhai et al. (US)	2025	USA	326	.59	FoMOS	BSMAS	NR	NR	No	7
Elhai et al. (Italy)	2025	Italy	433	.52	FoMOS (IT)	BSMAS	NR	NR	No	7
Servidio et al.	2025	Italy	356	.41	FoMOS (IT)	BSMAS	NR	NR	No	7
Servidio et al.	2026	Italy	625	.40	FoMOS (IT)	BSMAS	NR	NR	No	7
Al-Abyadh	2025	Saudi Arabia	470	.54	FoMOS (AR)	PSMU Scale	NR	NR	No	7
Varchetta et al.	2023	Spain	589	.41	FoMOS (ES)	BSMAS	.83	.79	No	8

Note. FoMOS = Fear of Missing Out Scale (Przybylski et al., 2013). AR = Arabic; CH = Chinese; DE = German; ES = Spanish; IT = Italian; TR = Turkish. BSMAS = Bergen Social Media Addiction Scale; BSNAS = Bergen Social Networking Addiction Scale; PMSMUAQ = Problematic Mobile Social Media Use and Addiction Questionnaire; PSMU Scale = Problematic Social Media Use Scale; TARS = Technology Addiction Rating Scale. All correlations are Pearson rat the FoMO × PSMU pairing. NR = not reported. COVID = data collected March 2020–December 2021. JBI = JBI Critical Appraisal Checklist score (max = 8).

^b^ PSMU α = .69 in Servidio et al. (2022); low internal consistency sensitivity analysis conducted (see Table 1).

5. Discussion

The central result of this synthesis is unambiguous: FoMO is a large, cross-culturally stable predictor of compulsive social media use, with a pooled r = .49 that held across nine countries, five distinct PSMU instruments, and all six pre-specified sensitivity analyses. This places FoMO among the most consistently supported psychological predictors of PSMU documented in the individual-differences meta-analytic literature a finding with both explanatory significance and a direct research agenda. Three pre-registered hypotheses were examined; H1 was decisively supported, and H2 and H3 produced instructive null results whose correct interpretation requires understanding the statistical constraints of the present synthesis.

5.1 Principal Findings

The primary meta-analytic estimate r = .49, 95% CI [.44, .54], z = 20.69, p < .001 constitutes a medium-to-large effect by Gignac and Szodorai's (2016) individual-differences benchmarks, indicating that FoMO accounts for approximately 24% of the variance in compulsive social media use across the pooled sample. H1 is supported without qualification. The 95% prediction interval (r [.30, .68]) is, in this respect, more informative than the point estimate: it establishes that even in the least favourable comparable population, the true FoMO–PSMU association is expected to remain large a lower bound of r = .30 corresponding to the large-effect threshold for individual-differences research (Gignac & Szodorai, 2016). This prediction interval answers the generalisability question directly. It indicates that the FoMO–PSMU association is not a contingent, context-specific finding nor an artefact of student sampling, Western cultural context, or pandemic conditions, but rather a replicable feature of the relationship between social loss sensitivity and compulsive digital monitoring

across the full range of populations represented in this literature. The z-statistic of 20.69, derived from k = 19 studies, provides decisive and well-powered evidence against the null.

This estimate is higher than previous meta-analytic estimates in more restricted samples Jing et al. (2025); Fioravanti et al. (2021) both found positive pooled associations, but their syntheses were limited largely to student populations and moderators were not systematically tested. The present estimate of r = .49 across diverse ages, nine countries, and five distinct PSMU instruments with the BSMAS used in 15 of 19 studies (79%) providing internal instrument consistency across the majority of the corpus substantially extends the generalisability of those prior findings. The temporal stability of the pooled estimate, confirmed by the cumulative meta-analysis across the 2022–2026 publication window, further indicates that the effect has not shrunk or shifted with increasing literature accumulation a pattern associated with inflated early estimates in some meta-analytic domains (Smaldino & McElreath, 2016).

The intensity of the primary estimate was systematically verified across all six pre-specified sensitivity analyses. The leave-one-out procedure produced estimates ranging from r = .47 to r = .50, all $p < .001$ and all I^2 between 79.69% and 91.53%, confirming that no single study drove the result. Excluding the high-leverage outlier Zhao et al. (2022) the sole COVID-era study, the largest observed correlation (r = .75), and the only study using the PMSMUAQ reduced the pooled estimate to r = .47, 95% CI [.44, .51], with I^2 decreasing from 90.84% to 79.69%. Excluding the low internal consistency study (Servidio et al., 2022; PSMU $\alpha = .69$) and jointly excluding all three Servidio et al. studies for potential sample overlap each yielded r = .50. Direction and magnitude were preserved across all specifications: the primary finding is stable.

5.2 Heterogeneity and Its Primary Source

Substantial between-study heterogeneity was observed: $Q(18) = 506.12$, $p < .001$, $I^2 = 90.84\%$, 95% CI [83.13%, 95.47%], $\tau^2 = 0.0092$, SE = 0.0035. This level of heterogeneity, substantially exceeding the 75% high-heterogeneity threshold (Higgins et al., 2003), was anticipated a priori given the diversity of populations, cultural contexts, and PSMU instruments in the synthesis. Its presence is not a methodological problem to be minimised but a substantive signal to be explained, and the moderator programme was designed precisely for this purpose.

The pre-registered moderator programme was conducted first. Study quality did not significantly moderate effect size (PROSPERO Additional Outcome 5): $QM(1) = 0.06$, $p = .801$, $R^2 = 0.00\%$, with all 19 studies scoring 7–8 out of 8 on the JBI Critical Appraisal Checklist. Geographic region (Italy vs. non-Italy; $QM = 1.57$, $p = .210$, $R^2 = 3.86\%$) and sample type (student vs. community; $QM = 0.45$, $p = .501$, $R^2 = 0.00\%$) were both non-significant exploratory moderators. The predominance of Italian samples (k = 8, 42%) attributable partly to an active research group producing multiple studies did not drive the overall estimate, as confirmed by the joint exclusion of all three Servidio et al. studies yielding r = .50. The pre-registered programme therefore accounted for effectively none of the observed variance, directing attention to the post-hoc investigation that followed.

The most consequential moderator identified was COVID-19 data collection context, an exploratory post-hoc variable added following the identification of Zhao et al. (2022) as a high-leverage outlier across four influence diagnostic indices (DFFITS, Cook's distance, externally studentised residuals, τ^2 deletion). The COVID-era variable accounted for $R^2 = 60.62\%$ of between-study variance by far the largest explanatory source identified in this

synthesis (QM = 23.26, $p < .001$). The single COVID-era study (Zhao et al., 2022) produced an observed r = .75, 95% CI [.73, .77], compared with the pooled non-COVID estimate of r = .47, 95% CI [.44, .51], a difference of approximately .28 correlation units corroborated by the factor-coded model (QM = 14.74, $p < .001$, $R^2 = 48.72\%$).

This finding demands careful and honest interpretation. With k = 1 COVID-era study, the difference cannot be treated as a formally established moderator effect it represents, at least in part, a single-study outlier result, and the .28 difference may reflect study-specific variance (including Zhao et al.'s use of the PMSMUAQ, distinct from the BSMAS used in all other included studies) as much as a genuine contextual amplification. Critically, however, the Zhao et al. (2022) finding should not simply be treated as noise to be controlled for it is precisely the empirical pattern that a loss-aversion account predicts. If FoMO-driven checking is governed partly by the asymmetric psychological weight of potential social loss, then conditions that objectively maximise the cost of disconnection should produce the largest effects in the literature. The fact that the single study conducted during the period of peak social disruption when online monitoring had become the principal means of maintaining relationships, social awareness, and emotional support (Cheng & Lau, 2022) produced both the largest observed correlation and accounted for 60.62% of between-study variance is directionally consistent with this prediction in a way that purely motivational or social comparison accounts of FoMO cannot as parsimoniously accommodate. The .28 difference between COVID and non-COVID pooled estimates is not noise; it is a theoretically predicted signal, even if k = 1 means it cannot yet be treated as an established finding. Replication with multiple COVID-era studies using standardised PSMU instruments is required before contextual amplification can be treated as established rather than plausible.

5.3 Age Moderation:

H2 predicted that the FoMO–PSMU association would be stronger in younger samples, on the theoretical grounds that adolescence and emerging adulthood are characterised by heightened peer evaluation sensitivity, acute social comparison processes, and incomplete development of self-regulatory capacities (Blakemore & Mills, 2014; Steinberg, 2008). Neither the continuous meta-regression of mean sample age ($QM(1) = 0.0000$, $p = .995$, $b = 0.0000$, $R^2 = 0.00\%$) nor the categorical age-group omnibus test ($QM(2) = 2.27$, $p = .322$, $R^2 = 2.97\%$) supported this prediction. H2 is not supported.

It is essential to interpret this null result accurately rather than prematurely. The descriptive subgroup point estimates $r = .34$ for adolescents ($k = 1$), $r = .46$ for young adults ($k = 13$), $r = .46$ for adults ($k = 5$) show no attenuation of the effect from young adult to older adult samples, which is contrary to the developmental hypothesis. Moreover, the teenage subgroup comprised only a single research (Abbouyi et al., 2026; N = 2,202), which falls short of the predetermined criterion of $k \geq 5$ for formal inference. The teenage point estimate of $r = .34$ is a correlation from a single research rather than a meta-analytic estimate; hence, comparisons with young adult or adult subgroups should not be construed as evidence of developmental moderation.

Three methodological constraints qualify the null result. First, statistical power for moderator detection at $k = 19$ is limited; simulation evidence indicates that detecting moderator effects of moderate size with adequate power typically requires $k \geq 40–50$ (Hedges & Pigott, 2004). The null age result is therefore appropriately described as a power-constrained non-finding rather than evidence of a true absence of moderation. Second, 13 of 19 studies sampled young adult participants, producing a narrow between-study range of mean sample ages and severely restricting the variance available for age regression to detect any linear gradient.

Third and this is the theoretically interesting reading of the null the near-identical r = .46 in both young adult and adult subgroups raises the possibility that loss-aversion-driven threat monitoring is not primarily a developmental phenomenon but a broadly operative mechanism across the adult age range. That the effect is equally large in samples with mean ages extending well into adulthood is more consistent with a trait-level cognitive account of FoMO than with a purely developmental account premised on age-limited regulatory deficits. Whether the association differs meaningfully in the 13–17 developmental window remains the single most important unresolved empirical question in the age moderation literature, and it cannot be addressed without a substantially larger adolescent evidence base.

5.4 Gender Moderation:

H3, treated as exploratory, predicted stronger associations in more female-dominant samples, drawing on the relational self-construal account (Cross & Madson, 1997) and evidence of greater female social media intensity and social comparison engagement (Andreassen et al., 2017; Shannon et al., 2022). The meta-regression was non-significant: $QM(1) = 0.36$, $p = .551$, $b = -0.0010$, $SE = .0016$, $R^2 = 0.00\%$. H3 is not supported.

Two constraints limit the interpretive value of this null, and one of them is methodological in a way that the field should recognise more broadly. The first is statistical power: at k = 19, continuous moderator detection requires effect sizes larger than those reliably produced in the moderation literature (Hedges & Pigott, 2004), and the negative, near-zero regression coefficient ($b = -0.0010$) is indistinguishable from zero. The second and more fundamental is a construct validity problem with the test itself. Between-study regression of the percentage of female participants on pooled effect size is a weak proxy for the individual-level hypothesis that theory actually specifies. The relational self-construal account (Cross & Madson, 1997) predicts that individuals whose identity is more strongly organised around

social connection will show stronger FoMO-driven compulsive monitoring. This is an individual-level prediction; testing it at the study level by regressing aggregate gender composition on aggregate effect size is an ecological procedure that cannot address the hypothesis as stated, is vulnerable to aggregation artefacts, and would be expected to produce null results even if the individual-level effect were real. The appropriate test requires primary studies to report gender-stratified FoMO–PSMU correlations or formal individual-level moderation analyses a reporting practice currently absent from the included literature. This null result is therefore informative about the absence of a between-study gender composition effect on pooled correlations, but is substantively uninformative about whether gender moderates the FoMO–PSMU association at the level of individual psychology. The distinction matters because it means H3 is not empirically resolved by the present synthesis it is deferred to future research with the correct design.

5.5 Publication Bias

Evidence for publication bias was weak and convergent across all six assessment methods. Funnel plot inspection indicated broad symmetry centred on $r \approx .49$, with Zhao et al. (2022) as a clear right-tail outlier consistent with its COVID-era status. Egger's test was non-significant ($z = -1.83$, $p = .067$); Begg's rank correlation was similarly non-significant ($\tau = -0.12$, $p = .489$). The exploratory PET and PEESE intercepts $b = 0.62$, 95% CI [.474, .767] and $b = 0.55$, 95% CI [.459, .633] respectively are both consistent with a true non-zero effect after correction for small-study bias. Duval and Tweedie's trim-and-fill procedure identified six imputed studies on the right side of the funnel, yielding an adjusted estimate of $r = .53$, 95% CI [.49, .58] larger than, not smaller than, the observed primary estimate. Right-side imputation is contrary to the conventional publication bias scenario in which small null studies are suppressed, creating left-side funnel asymmetry; it is instead consistent with

residual heterogeneity driven by the single COVID-era outlier pulling the distribution rightward. The trim-and-fill result, often misread as evidence of bias when it produces an upward adjustment, should be interpreted here as a heterogeneity indicator rather than a bias indicator. Convergent evidence across six methods including the two most analytically conservative (PET, PEESE) indicates that the primary estimate of r = .49 is unlikely to be substantially inflated by selective reporting.

5.6 Self-Esteem and Platform Type: A Narrative Synthesis

We reported two pre-specified moderators (self-esteem and platform type) narratively as pre-specified according to PRISMA 2020 Item 24 (Page et al., 2021) and required a protocol amendment (Version 2.0, May 2026, PROSPERO CRD420261322847.

Two studies measured self-esteem using the Rosenberg Self-Esteem Scale, a validated instrument (Gori et al., 2023; Sommantico et al., 2023; k = 2). The two studies showed that low self-esteem was related to high problematic social media use (PSMU) among groups with high fear of missing out (FoMO) consistent with the claim that low self-esteem makes people more vulnerable to social exclusion and comparison cues (Servidio et al., 2024). Both studies showed that low self-esteem was related to higher problematic social media use (PSMU) in populations with high fear of missing out (FoMO), thereby corroborating the idea that self-esteem deficits increase sensitivity to social exclusion and comparative cues (Servidio et al., 2024). Three further studies assessed conceptually related but operationally distinct constructs self-construal and loneliness that could not be recoded as self-esteem equivalents without construct invalidity. With k = 2 and no replication of the exact operationalisation, no quantitative conclusion is warranted. Self-esteem moderation of the FoMO–PSMU association is not a peripheral concern lower self-esteem specifically heightens the perceived cost of social exclusion, which is precisely the psychological mechanism through which loss aversion should amplify FoMO-driven checking. It therefore

represents the single most theoretically motivated and empirically unresolved moderator hypothesis remaining in this literature and warrants immediate targeted primary investigation.

Seventeen of 19 studies used platform-agnostic measures (mostly the BSMAS) in terms of platform type, which did not allow for meaningful comparison of FoMO–PSMU associations across specific platforms. Only one study employed a single-platform measure (Servidio et al., 2026). The prediction that visually evaluative platforms Instagram, TikTok amplify loss-aversion-driven social comparison cues and thereby strengthen the FoMO–PSMU link relative to text-dominant or utility-oriented platforms (Meier & Reinecke, 2020; Vogel et al., 2014) remains formally untested at the meta-analytic level. The predominant use of platform-agnostic PSMU instruments is a structural limitation of the field, not merely of this review. Future primary research must employ platform-specific PSMU measures if between-study platform variance is ever to be sufficient for this moderation to be examined in synthesis.

5.7 Prospect Theory and the Loss-Aversion Account

The overall pattern of results a large, cross-culturally stable association, contextual amplification specifically under the conditions that maximise the cost of social disconnection, and the absence of a systematic age gradient across adulthood is coherently and parsimoniously interpretable within the Prospect Theory framework advanced in the Introduction. Kahneman and Tversky's (1979) principle of loss aversion proposes that losses carry greater psychological weight than equivalent gains, producing a motivational asymmetry that renders loss-avoidance behaviours more urgent, more persistent, and more resistant to inhibition than equivalent gain-seeking behaviours (Tversky & Kahneman, 1991). Applied to social media, FoMO functions as a loss-anticipation state: platform updates signal potential social losses missed gatherings, unobserved peer milestones, untracked relationship

developments and the asymmetric weight assigned to those potential losses amplifies both the urgency to check and the psychological difficulty of disengaging.

Three specific features of the data are consistent with this account in ways that competing motivation-only frameworks cannot as parsimoniously accommodate. First, the cross-cultural stability of $r \approx .47–.49$ across nine countries and four continents is consistent with loss aversion being a broadly operative feature of human social cognition, established across decades of behavioural economics research as a robust cross-cultural phenomenon (Tversky & Kahneman, 1991), rather than a culturally specific vulnerability pattern. A social comparison account, by contrast, would predict stronger moderation by cultural individualism–collectivism indices given differences in self-construal norms moderation that is not apparent in the geographic region analysis ($QM = 1.57$, $p = .210$). Second, the COVID-19 amplification approximately .28 correlation units is precisely the directional pattern that loss aversion predicts: conditions that objectively elevate the cost of social disconnection should produce larger effects, and the single study conducted under those conditions did. Third, the absence of a detectable age gradient across the 18+ range is inconsistent with a purely developmental account of FoMO in which regulatory immaturity is the primary driver, but is consistent with loss-aversion-driven social monitoring being a stable adult psychological mechanism whose intensity depends more on perceived social stakes than on developmental stage. This context-sensitivity the systematic amplification of the association precisely when social disconnection costs are objectively elevated is the critical discriminating prediction: trait-level accounts such as general negative affectivity would predict uniformly high FoMO–PSMU correlations across contexts, whereas loss aversion specifically predicts associations that scale with perceived social stakes.

It is essential to reiterate that Prospect Theory is applied here as a theoretical interpretive lens, not a measured construct. The framework generates specific, falsifiable predictions that the present data cannot test but that constitute a direct research agenda: that individual-level loss aversion scores should mediate or moderate the FoMO–PSMU association beyond what social comparison sensitivity or relatedness needs account for; that experimentally induced social disconnection threat should produce acute increases in compulsive checking beyond baseline; and that platform features specifically designed to increase the salience of social loss cues disappearing content, real-time activity indicators, read receipts, publicly visible engagement counts should amplify the FoMO–PSMU association beyond platforms without these features. Each prediction is empirically tractable with existing methods and represents a falsifiable test of the loss-aversion account that cross-sectional survey evidence cannot provide.

Behavioural addiction frameworks particularly Griffiths' (2005) components model offer a complementary rather than competing account. The negative reinforcement cycle, in which checking temporarily alleviates exclusion anxiety and reinforces further checking, is structurally consistent with both the addiction model and the loss-aversion account. These frameworks operate at different explanatory levels: Griffiths identifies the behavioural architecture of compulsive use; Prospect Theory identifies the cognitive-affective mechanism that makes anticipated social loss disproportionately compelling in the first instance. Integrating both levels the motivational asymmetry that initiates checking and the negative reinforcement cycle that sustains it provides a more complete account of the FoMO–PSMU association than either framework offers independently, and points toward an intervention logic that targets both the environmental trigger and the reinforcement schedule simultaneously.

6 Limitations

Six limitations require direct acknowledgement. First, all 19 included studies employed cross-sectional designs, which structurally preclude causal inference. Whether FoMO drives PSMU, PSMU drives FoMO, or both are jointly influenced by unmeasured third variables such as trait negative affect, attachment insecurity, or chronic loneliness cannot be resolved from the present synthesis. The meta-analytic estimate of r = .49 is a precise, well-powered covariance estimate, not a causal effect. Emerging longitudinal evidence suggests bidirectional dynamics (David & Roberts, 2023), which the present synthesis cannot examine but which future longitudinal meta-analyses should target specifically. Second, single-reviewer screening, data extraction, and quality assessment were employed throughout, as pre-disclosed in the PROSPERO protocol (CRD420261322847). Pilot screening, pre-registered extraction forms, and full OSF archiving were implemented as mitigation strategies, but the risk of unsystematic extraction error that dual-reviewer processes reduce cannot be fully eliminated. Third, the English-language restriction (PROSPERO CRD420261322847) may modestly underrepresent non-Anglophone literature; although the nine-country, four-continent coverage substantially reduces this concern, studies from large social media markets in South and Southeast Asia remain absent from the evidence base. Fourth, with k = 19 studies, statistical power for moderator detection is limited; null findings for age and gender should not be interpreted as evidence of a true absence of moderation, and both hypotheses remain empirically open (Hedges & Pigott, 2004).Fifth, the adolescent subgroup was based on a single study (k = 1; Abbouyi et al., 2026), and thus no pre-registered formal test of developmental moderation in the 13–17 window could be run; the descriptive estimate of r = .34 is the observed correlation from a single study, rather than a population parameter. Sixth, the COVID-era moderator effect is based on k = 1 study. The elevated effect in Zhao et al. (2022) may be due to the pandemic-context amplification,

instrument-specific variance (PMSMUAQ vs.BSMAS), or cultural specificity in the Chinese sample, or a combination of these three. Those explanations are not separable from a single data point.

6.1 Implications for Research

Four research priorities emerge with direct evidential grounding from the present findings. First, longitudinal designs with cross-lagged panel modelling and ideally random-intercept cross-lagged panel models (RI-CLPM; Hamaker et al., 2015) to separate within-person dynamics from between-person confounds are needed to establish the temporal directionality of the FoMO–PSMU relationship at the level of individual change. Cross-sectional meta-analysis cannot resolve this question regardless of sample size. Second, primary studies must routinely report gender-stratified FoMO–PSMU correlations or formal individual-level moderation analyses: aggregate between-study gender composition is an insufficient and potentially misleading proxy for the individual-level relational self-construal processes that theory specifies, and the field cannot resolve H3 without changing its reporting practices. Third, targeted recruitment of adolescent samples using validated FoMO and PSMU instruments is an immediate priority the current $k = 1$ in the 13–17 window means the developmental moderation question that motivated H2 is entirely unresolved, and it is arguably the most policy-relevant moderation question in the literature given the volume of regulatory attention directed at adolescent social media use. Fourth, primary studies must begin employing platform-specific PSMU instruments alongside platform-agnostic ones; the visual comparison hypothesis that Instagram and TikTok amplify loss-aversion-driven checking relative to text-dominant platforms is theoretically motivated, practically important, and completely untestable from existing meta-analytic evidence.

6.2 Implications for Practice

A pooled r = .49, stable across cultures and all sensitivity specifications, and with a prediction interval lower bound that remains large, carries direct and non-trivial clinical and policy implications. At the clinical level, individuals with elevated FoMO represent a plausibly identifiable high-risk group for PSMU, and routine FoMO screening using the freely available, psychometrically validated 10-item Fear of Missing Out Scale (Przybylski et al., 2013) is warranted in digital wellbeing services, university student counselling, and primary care contexts where social media difficulties are presented. Cognitively, interventions should target the threat-monitoring cycle identified in the mechanism analysis: stimulus control strategies removing applications from home screens, disabling push notifications, establishing device-free time windows reduce the frequency of loss-signalling cue exposure and directly address the environmental trigger of loss-aversion-driven checking without requiring volitional inhibition against a persistent psychologically asymmetric impulse. Exposure and response prevention adapted for social media compulsions, and cognitive restructuring targeting the catastrophising of social exclusion and informational deprivation, are theoretically aligned with the FoMO–PSMU mechanism and represent logical clinical translations of the present findings (Brand et al., 2022).

At the platform and policy level, the present findings carry an argument that goes beyond conventional digital wellbeing guidance. Design features that specifically increase the salience and urgency of social loss cues real-time activity status indicators, disappearing content with countdown timers, publicly visible engagement metrics, read receipts do not merely increase engagement through reward; under a loss-aversion account, they actively exploit the motivational asymmetry between anticipated loss and equivalent gain, making platform disengagement disproportionately costly relative to the actual informational value of

any individual check. This is a structurally different regulatory argument from simply reducing screen time. Regulatory frameworks including the UK Online Safety Act, EU Digital Services Act, and emerging platform design codes from communications regulators should evaluate platform features not only for their capacity to maximise engagement but for their capacity to exploit loss-aversion-driven monitoring. Requiring platforms to provide granular user controls to disable loss-signalling features by default would address the environmental conditions that amplify FoMO-driven compulsive engagement at the system level rather than placing the full regulatory burden on individuals attempting to inhibit a psychologically asymmetric drive.

7. Conclusion

This pre-registered systematic review and meta-analysis established a large, cross-culturally stable, and methodologically robust positive association between Fear of Missing Out and compulsive social media use: r = .49, 95% CI [.44, .54], across 19 studies and 10,781 participants from nine countries. The prediction interval lower bound of r = .30 representing the expected association in the least favourable comparable population indicates that the FoMO–PSMU relationship is not a contingent, sample-specific finding but a replicable feature of the relationship between social loss sensitivity and compulsive digital monitoring across the populations studied. The association held across all six pre-specified sensitivity analyses, showed no meaningful evidence of publication bias across six convergent assessment methods, and was exploratorily amplified under COVID-19 pandemic conditions in a pattern directionally consistent with the loss-aversion account in which conditions that maximise the cost of social disconnection should produce the strongest effects. Pre-registered age and gender moderation were not supported, but both null results are constrained by the

statistical power available at k = 19 and by a fundamental methodological limitation of between-study gender regression as a test of individual-level moderation hypotheses; neither hypothesis is empirically resolved. The Prospect Theory framework of social loss aversion provides a theoretically coherent, cross-culturally parsimonious, and empirically generative account of the consistency and context-sensitivity of the FoMO–PSMU association and generates a specific, falsifiable research agenda for the longitudinal, experimental, and platform-level investigations that the field requires to move beyond meta-analytic synthesis and toward mechanistic understanding.

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