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Associations of internet use and specific patterns with cognitive function in older adults: a systematic review and meta-analysis

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Background: Global aging is accompanied by cognitive decline. While the "technological reserve" hypothesis suggests internet use may mitigate this, prior meta-analyses have not clarified the specific effects of different usage patterns. This study aims to systematically evaluate associations between distinct dimensions of internet use and cognitive function in older adults.
Methods: Conducted in accordance with PRISMA 2020 guidelines, we searched PubMed, Embase, CINAHL, PsycINFO, and Web of Science from inception to March 15, 2026. Two Reviewers independently extracted data. Pooled Odds Ratios (ORs) or Hazard Ratios (HRs) served as primary effect measures; Correlation coefficients (r) or standardized beta coefficients (β) were converted into unified OR-scale estimates for meta-analysis, acknowledging inherent limitations introduced by combining mixed effect measures from original studies.
Results: Thirty-one studies comprising 158,648 participants (cross-sectional and longitudinal observational designs) were included. The random-effects meta-analysis of 25 studies yielded a pooled OR of 1.49 (95% CI: 1.31–1.70), indicating general internet use was significantly associated with better cognitive function ($z = 5.97$, $P < 0.001$). Substantial heterogeneity was observed ($I^2 = 99.51\%$). A 95% prediction interval (1.15–1.93) was further calculated to quantify uncertainty. Subgroup analyses showed significant positive associations for social ($OR = 1.55$), entertainment ($OR = 1.46$), and instrumental use ($OR = 1.38$). However, meta-regression revealed no statistically significant differences among these categories ($F_{(2, 24)} = 0.36$, $P = 0.63$). Sensitivity analysis excluding outliers yielded a similar pooled point estimate, although substantial heterogeneity persisted. (pooled $OR = 1.46$, 95% CI: 1.29–1.67).
Conclusions: Internet use was positively associated with better cognitive function among older adults. This positive association was observed across social, entertainment, and instrumental internet use patterns. Given high between study heterogeneity and the observational nature of available evidence, further longitudinal and interventional research is needed to clarify whether diverse digital engagement may support healthy cognitive aging.
Systematic review registration: https://www.crd.york.ac.uk/PROSPERO/recorddashboard, identifier: CRD420261359423.

KEYWORDS
cognitive functioning, internet use, internet use types, meta-analysis, older adults

1 Introduction

The global population is aging rapidly. Based on projections from the UN's *World Population Prospects 2024*, the proportion of the aging population globally is estimated at range from 11.2% to 11.8% (1). According to the *Global Health and Aging* report, by 2050, the number of people aged 60 years and older will surpass 2 billion, and the number of people aged 80 and over is expected to triple to 426 million—most of whom will reside in low- and middle-income countries (2). Life expectancy has nearly doubled over the past 150 years, reaching 73.3 years in 2024 (3). Nevertheless, despite increased longevity, the proportion of life spent in good health has remained stagnant. The added years are frequently accompanied by chronic conditions and progressive declines in physical and cognitive functioning (4). Cognitive function has a comprehensive and profound impact on older adults. It goes far beyond memory, directly affecting their quality of life, physical health, and even personal safety. Key consequences include the loss of independence in daily living, the deterioration of language and social abilities, and direct threats to physical wellbeing and safety. Some studies suggest that sufficient environmental stimulation leads to better cognitive function, while cognitive decline stems from the long-term disuse of cognitive abilities (5, 6). Since the turn of the century, internet usage has been transforming people's lifestyles. This trend is also evident among the older adults, who widely use the internet for socializing, shopping, and entertainment. There are even software applications specifically designed to improve cognitive function in older adults. Studies that juxtapose technology-based interventions with traditional programs have highlighted the exceptional efficacy of digital solutions. The findings reveal that the former outperform the latter, offering more substantial benefits in terms of boosting cognitive function and fostering a better quality of life (7–9). The technological reserve hypothesis provides one plausible mechanistic framework to interpret these associations. The core premise of the technological reserve hypothesis is that the continuous use of digital technologies may help the brain build a "cognitive reserve," which could correlate with slower age-related cognitive decline and reduced odds of cognitive impairments such as dementia (10). However, interpreting this association requires caution due to plausible alternative explanations. Primarily, the relationship may be subject to reverse causality; individuals with better baseline cognitive function and higher socioeconomic status are naturally more capable of adopting and mastering complex digital technologies, rather than the technology itself driving cognitive improvement. Furthermore, prior syntheses have largely treated internet use as a monolithic exposure, failing to disentangle whether specific active engagements (e.g., learning, socializing) offer unique cognitive benefits distinct from passive consumption or general healthy lifestyle factors. Driven by social motivations, such as staying connected with family and integrating into society, older adults are often willing to overcome operational barriers to adopt digital tools (11). Even if they may no longer learn entirely new and complex technologies, they can rely on the technological reserve accumulated over past decades, or utilize technology to compensate for their impaired memory and executive functions (12). Notably, a recent large-scale meta-analysis by Benge and Scullin supports this protective role of general digital technology use (13). However, this synthesis treated digital technology use as a broad, unified exposure and did not quantify heterogeneity across distinct types of internet-based activities (14). A second relevant systematic review by Yuan et al. examined internet use and cognitive function among middle-aged and older adults, yet its sample combined middle-aged and older participants and primarily evaluated overall internet engagement rather than separating discrete online activity categories (15). Emerging primary studies indicate that the cognitive correlates of internet use are not homogeneous and vary by the specific type of online activity. Different dimensions of online activities—such as social interaction, information seeking, or entertainment consumption—may exert differential effects on the brain through distinct cognitive mechanisms. While these two prior meta-analyses advanced evidence on digital technology and cognition, no existing quantitative synthesis has specifically stratified and compared effect sizes across differentiated internet activity types, with a strict focus on older adults (13). Therefore, this study aims to conduct a meta-analysis to explore associations between different types of internet use and cognitive function in older adults. We test two *a priori* hypotheses: (1) overall internet use is positively associated with better cognitive function among older adults; (2) different patterns of internet use may show differential magnitudes of association with cognitive outcomes.

2 Methods

This meta-analysis was performed following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 reporting checklist15. The study protocol was prospectively registered on the International Prospective Register of Systematic Reviews (PROSPERO) under registration number CRD420261359423.

2.1 Literature search

We conducted a systematic search of PubMed, Embase, CINAHL, PsycINFO, and Web of Science from inception to 15 March, 2026. The search strategy incorporated free keywords and Medical Subject Headings (MeSH) terms related to internet use and cognitive function. The detailed search strategy is presented in Supplementary Table S1. Only English-language publications were included.

In addition to database retrieval, we manual screening the reference lists of relevant reviews and included studies to identify further qualified publications.

2.2 Inclusion and exclusion criteria

Systematic review and meta-analysis were conducted following the PRISMA guidelines. To ensure the homogeneity and relevance of the included evidence, studies were selected if they met the following PICOS criteria:

2.2.1 Population

We included studies recruiting community-dwelling older adults with a mean age $\geq$ 60 years. Studies were not excluded merely if the mean sample age was slightly below 60 years, provided that a substantial proportion of participants were $\geq$60 years old and the study target population was older adults. We selected 60 years as the age cutoff threshold, consistent with the standard definition adopted by WHO and many geroscience epidemiological studies for older adult populations (16). Studies focusing solely on clinical populations (e.g., participants diagnosed with dementia) were excluded.

2.2.2 Intervention/Exposure: internet use

Studies had to specifically report 'internet use' (e.g., browsing, searching, email) as a distinct variable. Studies that only reported 'computer use' or 'smartphone ownership' without differentiating internet-based activities were excluded to isolate the cognitive stimulation effect from basic device operation skills.

2.2.3 Comparison

Older adults with no regular internet use.

2.2.4 Outcomes

Objective neuropsychological assessments of cognitive function. For this review, cognitive function was defined as performance across distinct cognitive domains, including global cognition, memory, executive function, attention, and processing speed. We excluded studies reporting only diagnostic binary outcomes (e.g., incident dementia or incident mild cognitive impairment), to focus exclusively on continuous objective cognitive test scores. Eligible outcomes included cross-sectional cognitive test scores measured at a single time point, as well as longitudinal assessments of cognitive decline over follow-up.

2.2.5 Study design

This review specifically focused on observational study designs. To ensure methodological rigor, only peer-reviewed observational studies were eligible for inclusion. This encompassed cross-sectional studies and longitudinal studies. We accounted for differences in causal inference capacity across observational designs when interpreting pooled estimates. Cross-sectional studies can only identify associations and cannot establish temporality between exposure and outcome, whereas longitudinal cohort studies support temporal inference. Ecological studies, case reports, case series, and intervention-based randomized controlled trials (RCTs) were excluded.

For duplicate publications, only the report with the largest sample was retained. If the data set had been used more than once, the publication most relevant and appropriate for the current review was included.

2.3 Data extraction

Data extraction was conducted independently by two reviewers, with any discrepancies resolved through discussion or adjudication by a third senior reviewer. The extraction protocol encompassed key study characteristics, including the first author, publication year, country of origin, and study design, as well as population demographics such as mean age and sample size. Furthermore, we systematically extracted the primary outcomes and the specific instruments used for assessment. For the statistical analysis, we prioritized collecting the adjusted effect sizes and the list of covariates adjusted for in the multivariate models. To ensure methodological rigor, we also extracted scores pertinent to the quality assessment scale, and in instances where data were not explicitly reported, we attempted to calculate effect sizes from available raw data or contacted corresponding authors via email; outcomes for which data remained unavailable were excluded from the quantitative synthesis.

2.4 Study quality evaluation

We appraised methodological quality of eligible articles with the National Institutes of Health Study Quality Assessment Tool (17). Fourteen evaluation domains were covered, spanning research question clarity, population definition, recruitment participation rate, between-group comparability, sample-size justification, temporality of exposure-outcome association, reliability and validity of indicator measurement, outcome assessor blinding, follow-up attrition, and confounder adjustment. Per-item ratings fell into five categories: "Yes," "No," "Cannot determine," "Not applicable," and "Not reported." The included studies were independently assessed and categorized as Good, Fair, or Poor. Studies were rated as Good when most key items were judged to be at low risk of bias, confounders were adequately adjusted for, exposure and outcome measurements were reliable, and no critical flaws existed that could invalidate the findings. Studies were rated as Fair when several items were rated as unclear or when methodological limitations were present but none were severe enough to completely undermine the study conclusions. Studies were rated as Poor when critical domains were judged to be at high risk of bias—for example, due to lack of adjustment for major confounders or unreliable exposure and outcome measurements—and when important methodological weaknesses substantially compromised the credibility of the results. Dual independent rating was performed by two investigators, with inconsistent ratings reconciled either by mutual discussion or arbitration from a third senior reviewer. A prespecified sensitivity analysis was planned to exclude this single "Poor"-rated study to assess the robustness of the pooled effect estimate.

2.5 Publication bias assessment

Publication bias was assessed using funnel plots and Egger's regression test to evaluate small-study effects. We recognize that

the interpretation of these tests may be limited in the presence of high heterogeneity.

2.6 Sensitivity analysis

To assess the robustness of the pooled effect estimates and ensure that the results were not driven by specific data points, we conducted sensitivity analyses based on pre-defined criteria for identifying potential outliers and influential studies prior to analysis. Studies were considered potential statistical outliers if their effect estimates [Odds Ratios, (OR)] deviated substantially from the central tendency of the included literature, specifically those exceeding a pre-established threshold for extreme effect sizes that might disproportionately skew the pooled estimate. Additionally, to evaluate the influence of study precision and statistical leverage, we targeted the studies representing the boundaries of the sample size distribution within our dataset by specifically selecting the studies with the smallest and largest sample sizes to test whether the pooled results were overly sensitive to extremes in statistical weight. We performed a leave-one-out sensitivity analysis by sequentially excluding these pre-identified studies—both individually and simultaneously—to verify the stability of the primary findings, whereby a significant change in the pooled effect size or its direction upon exclusion would indicate a lack of robustness in the overall conclusion.

2.7 Data analysis

All statistical syntheses were conducted in Stata/MP 16.0 (StataCorp LLC, College Station, TX, USA). Given the expected clinical and methodological diversity across studies, a random-effects model (Der Simonian and Laird method) was employed for all primary analyses. This model incorporates both within- and between-study variance components to produce conservatively pooled effect sizes and wider confidence intervals, making it appropriate even in the presence of substantial heterogeneity. Heterogeneity was quantified using the I^2 statistic and Cochran's Q test. We justified the pooled synthesis based on the consistency of the effect direction (i.e., protective association) across included studies, aiming to estimate the average effect size rather than a single common effect.

Pre-specified subgroup analyses were undertaken to explore potential sources of heterogeneity (e.g., cognitive assessment tools, study design, covariate adjustment). To further validate the robustness of our findings against high heterogeneity, we conducted sensitivity analyses by: (1) sequentially excluding outlier studies with extreme effect sizes; and (2) restricting the analysis to studies reporting original ORs to minimize bias from converted metrics.

Pre-specified hierarchical coding criteria were enforced throughout data extraction to safeguard analytical consistency and clinical relevance. Multiple cognitive test outcomes from a single primary study were pooled into composite effect sizes to eliminate overrepresentation bias. Effect-size signs were reversed for metrics with inverted measurement directions to standardize outcome interpretation across all included studies. When both correlation (r) and standardized beta (β) coefficients were available, fully adjusted β from maximally confounder-controlled regression models was preferentially abstracted. For studies reporting both cross-sectional baseline and longitudinal sustained internet-use data, only longitudinal follow-up estimates were selected to characterize chronic internet exposure (18). To resolve duplicate cohort overlap across multiple publications, unique-wave data was retained if available; otherwise, the most thematically relevant article was selected to avoid double-counting participants and maintain independent study samples.

To synthesize evidence from studies reporting either binary cognitive impairment outcomes or continuous cognitive test scores, we harmonized all effect estimates onto a common OR scale using validated transformation approaches. This method assumes continuous cognitive function represents a latent underlying trait, where binary cognitive impairment can be conceptualized as a threshold cut-off on this latent continuum.

Primary pooled effect sizes were expressed as ORs and Hazard Ratios (HRs). HR estimates were analyzed and reported separately and were not converted to OR or pooled within the OR meta-analysis. For publications without raw OR/HR, two types of effect metrics were retrieved and mathematically harmonized into OR equivalents using validated transformation methods: Pearson correlation coefficients (r), standardized regression coefficients (β). All conversions relied on the framework that first transformed the raw statistic into the standardized mean difference (*Cohen's d*), then converted d to OR using the relation $\ln(OR) = d \times \pi/\sqrt{3}$, assuming the latent continuous cognitive outcome followed a logistic distribution (19–21). The specific formulas are presented below. ①Standardized β: $OR = e^{\beta \times \pi/\sqrt{3}}$; ②Pearson r: first converted to $d = 2r/\sqrt{1-r^2}$, then $OR = e^{d \times \pi/\sqrt{3}}$, assuming bivariate normality. Log-transformed effect-size standard errors (SE) were computed to construct 95% confidence intervals (95% CIs). For quantitative pooling, all effect estimates were standardized onto a uniform OR scale, except for HRs, which were retained in their original form and not converted to ORs. A pre-specified sensitivity analysis was performed, restricted only to studies directly reporting raw ORs (without mathematical transformation), to assess the impact of effect-size harmonization on pooled estimates and heterogeneity.

2.8 Definition of internet use patterns

To address the specific patterns of internet use, we predefined three mutually exclusive categories of exposure: social, entertainment, and instrumental/informational use. Social internet use encompasses online social interactions, including social media engagement, video calls, and messaging. Entertainment internet use refers to leisure-oriented activities such as online gaming, streaming media, and general browsing. Instrumental/informational internet use includes utilitarian tasks like information searching, online banking, shopping, email communication, and work-related activities. For studies reporting mixed or multiple types of internet behaviors, classification was determined by the primary exposure construct defined in the original article; if no clear primary exposure was specified, the study was labeled as "mixed-use" and allocated to the

category reflecting the dominant behavior. All classification decisions were pre-specified prior to quantitative synthesis and independently double-checked by two reviewers. We acknowledge that internet use is a broad construct operationalized differently across studies (e.g., binary use vs. non-use, frequency, duration, or composite indices); therefore, we explored this heterogeneity via meta-regression across the three defined use-type categories.

For studies involving mixed internet use, classification was based on the specific exposure variable analyzed in relation to cognitive outcomes. If a study reported distinct effect sizes for different types of usage (e.g., separate regression coefficients for 'social networking' and 'entertainment'), these were treated as independent comparisons and categorized into their respective subgroups. We ensured that the same sample was not double-counted within the same subgroup analysis to avoid unit-of-analysis errors.

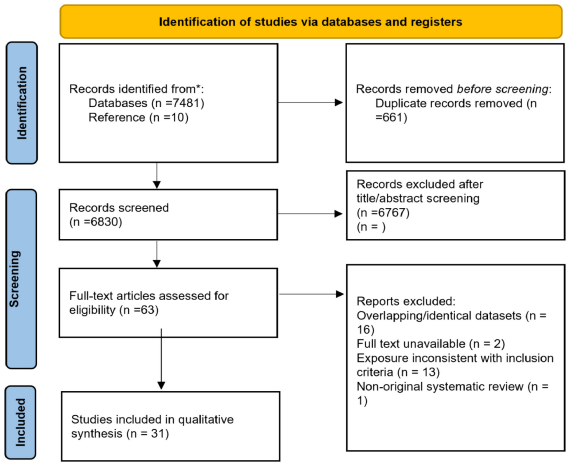

FIGURE 1
PRISMA flow diagram detailing the literature search and screening workflow. A total of 31 studies met all predefined inclusion criteria, of which 25 articles contained available quantitative data and were pooled in the final meta-analysis exploring the association between internet-use patterns and cognitive performance in older adults.

3 Results

3.1 Search results

The study screening flowchart is provided in Figure 1. In total, 7,491 unique citations were identified from electronic databases and hand-screened reference lists. After duplicate removal (n = 661) using EndNote software, 6,830 distinct records underwent preliminary title and abstract screening, whereby 6,767 irrelevant publications were excluded. The remaining 63 full-text articles were further assessed for formal eligibility; 32 were excluded owing to: shared identical study datasets (n = 16), inaccessible full-text resources (n = 2), non-compliant exposure/internet-use definition (n = 13), and systematic review design without original empirical data (n = 1). Ultimately, 31 studies fulfilled all eligibility requirements and were included in the present systematic review and meta-analysis.

3.2 Characteristics of included studies

A total of 31 studies were included in this review, comprising 11 longitudinal and 20 cross-sectional studies. These studies were conducted across 16 countries and regions on five continents. The majority of the studies originated from Asia (n = 14), with the largest proportion from China (n = 10) (22–31), followed by South Korea (n = 2) (32, 33), Japan (n = 1) (34), and Turkey (n = 1) (35). North America contributed eight studies, predominantly from the United States (n = 7) (14, 36–41) and one from Mexico (42). Europe was represented by seven studies, including two from Germany (43, 44), and single studies from Spain (45), Switzerland (46), and international collaborations involving Sweden–Netherlands (47), Germany–UK (48), and Greece–Canada (49). Additionally, one study was conducted in South America (Brazil) (18) and one in Oceania (New Zealand) (50). The sample sizes of the included studies ranged from 44 to 29,576 participants, aggregated total sample size of 158,648 participants. Detailed baseline features of included studies focusing on overall and subtype internet-use associations with cognitive function are summarized in Supplementary Tables S4, S5.

3.3 General internet use and cognitive function

Among the 31 studies included in the qualitative synthesis, only two met the criteria for potential meta-analysis by reporting HRs (24, 34). However, these two studies were not pooled due to the methodological inappropriateness of combining HRs with ORs or other effect sizes. Furthermore, pooling only two studies is generally considered statistically unfeasible and methodologically suboptimal for meta-analysis. Consequently, a narrative synthesis approach was adopted for this review. The two studies reporting longitudinal survival data showed positive associations between internet related technology use and cognitive outcomes among older adults. Imamura et al. observed that older ICT users had a significantly slower rate of cognitive decline (β =-0.09 vs. −0.18) and were associated with a lower risk of cognitive impairment (HR = 0.73, 95% CI 0.70–0.76) (34). Similarly, Li et al. reported that older adults who successfully crossed the digital divide during longitudinal follow-up and those who had already done so prior to tracking had significantly slower rates of decline in processing speed ($B = -1.98$, $P < 0.05$; $B = -2.62$, $P < 0.01$) and general cognitive function ($B = 3.50$, $P < 0.001$; $B = 3.13$, $P < 0.01$) (24). Notably, overcoming the digital divide was associated with lower risk of mild cognitive impairment (MCI) (HR = 0.43, 95% CI 0.29–0.62). Additionally, the decision to exclude the study by Atlas et al. (50) from the pooled analysis was primarily driven by the nature of the outcome data reported. This study presented results as continuous variables, whereas the primary outcomes of the remaining literature were reported as dichotomous variables. The absence of raw data necessary to convert these continuous outcomes into ORs created

a unavailable raw data, precluding its quantitative synthesis with the other studies. Furthermore, three additional studies (30, 33, 38) investigating the multidimensional aspects of internet usage were excluded from the meta-analysis due to their use of domain-specific metrics that were not directly comparable to the standardized global cognitive assessments employed in the rest of the literature.

Random-effects meta-analysis across 25 studies yielded a pooled ORs of 1.49 (95% CI 1.31–1.70), demonstrating that overall internet use was statistically significantly associated with better cognitive performance in older adults ($z = 5.97$, $P < 0.001$). Marked extremely high heterogeneity was observed across included research ($I^2 = 99.51\%$, $P < 0.001$; Figure 2). We further calculated the 95% prediction interval (PI) within the identical REML framework (Figure 3). Minor numerical optimisation differences for estimating between-study variance (tau^2) during prediction interval computation led to a slight change in the (I^2) estimate ($I^2 = 96.8\%$) in Figure 3. Both values demonstrated extreme heterogeneity, and the pooled effect size remained unchanged. The 95% prediction interval was 1.15–1.93, indicating a wide range of plausible true effect sizes across individual included studies. This large between-study variability prompted our pre-planned subgroup and sensitivity analyses to explore potential sources of heterogeneity.

3.4 Internet use types and cognitive function

Drawing upon prior published classification frameworks (33, 51, 52), all included internet-use indicators were grouped into three mutually exclusive categories: instrumental, social, and recreational activity. Instrumental internet use describes purpose-driven online operations to fulfill practical daily needs; social use comprises virtual communication and community-connected interactions; recreational use consists of leisure-focused online activities for entertainment. Multiple effect estimates from the same usage subtype within an individual study were aggregated into a single pooled value ahead of subgroup meta-analysis. Any uncategorized online activity indicators inconsistent with the three-class framework were omitted from stratified quantitative synthesis. Full descriptive information and extracted outcome data of eligible studies are listed in Supplementary Table S5.

Subgroup analyses were conducted to examine the potential moderating role of internet usage types. As illustrated in Figure 4, social internet usage demonstrated a statistically significant positive association with cognitive function among older adults ($OR = 1.55$, 95% CI 1.34–1.74). Similarly, entertainment usage showed a statistically significant positive association ($OR = 1.46$, 95% CI 1.21–1.72), albeit with a slightly smaller effect size compared to the social group. Instrumental usage also showed a statistically significant positive association ($OR = 1.38$, 95% CI 1.05–1.72). To formally test for differences between these subgroups, a meta-regression analysis was performed. The results indicated that the observed differences among the three usage types did not reach statistical significance ($F_{(2, 24)} = 0.36$, $P = 0.63$). This suggests that social internet usage had the numerically largest pooled OR estimate ($OR = 1.55$), followed by entertainment ($OR = 1.46$) and instrumental internet use ($OR = 1.38$). However, meta-regression found no statistically significant differences across these three categories ($F_{(2, 24)} = 0.36$, $P = 0.63$). It is important to note that a non-significant test result cannot prove equivalent association magnitudes; limited statistical power, potential misclassification and overlap between exposure categories mean genuine differences across usage subtypes cannot be ruled out by current evidence (See Supplementary Table S2 for details).

To ensure the robustness of our findings, we conducted a sensitivity analysis by excluding studies with small sample sizes ($n < 1{,}000$) (30, 36, 38) and those with lower methodological quality scores (22). Repeated the subgroup analysis on this restricted dataset yielded consistent results, with no statistically significant differences observed among the different types of internet use ($P > 0.49$). This suggests that comparable association magnitudes across domains are not driven by outliers or low-quality evidence. This suggests that comparable association magnitudes across domains are not driven by outliers or low-quality evidence.

3.5 Subgroup analysis

To investigate the sources of the substantial heterogeneity ($I^2 = 99.51\%$), we performed meta-regression analyses using study design and the extent of confounder control as covariates (Table 1, Model 1). The overall model was not statistically significant ($F_{(2, 22)} = 0.19, P = 0.82$), and neither study design ($P = 0.54$) nor confounder control ($P = 0.83$) emerged as a significant moderator. Consequently, the model accounted for a negligible proportion of the between-study variance ($Adj\ R^2 = -5.81\%$), with substantial residual heterogeneity remaining ($I^2_{res} = 96.10\%$).

Similarly, a second meta-regression model examined sample size and country income level (Table 1, Model 2). This overall model was also statistically non-significant ($F_{(2, 22)} = 0.74, P = 0.49$), indicating that these covariates failed to explain the variance in effect sizes. Specifically, neither sample size ($P = 0.361$) nor country income ($P = 0.518$) was a statistically significant moderator. Consistent with the first model, the explained variance was negligible ($Adj\ R^2 = -10.81\%$), and substantial residual heterogeneity persisted ($I^2_{res} = 96.45\%$).

We additionally conducted categorical subgroup analysis stratified by cognitive assessment tool, separating studies using the Mini-Mental State Examination (MMSE) vs. other domain-specific cognitive measurement tools (Figure 5). No statistically significant difference in pooled effect estimates was observed between subgroups ($P_{\text{between}-\text{group}} = 0.414$). The pooled OR was 1.32 (95% CI 1.17–1.49, $I^2 = 88.3\%$) for studies adopting MMSE, and 1.40 (95%CI 1.30–1.51, $I^2 = 97.7\%$) for studies using alternative cognitive instruments.

3.6 Sensitivity analysis excluding outliers and extreme sample sizes

To assess the robustness of the pooled effect estimate and the influence of individual studies, we conducted a series of sensitivity analyses. First, we sequentially removed studies identified as

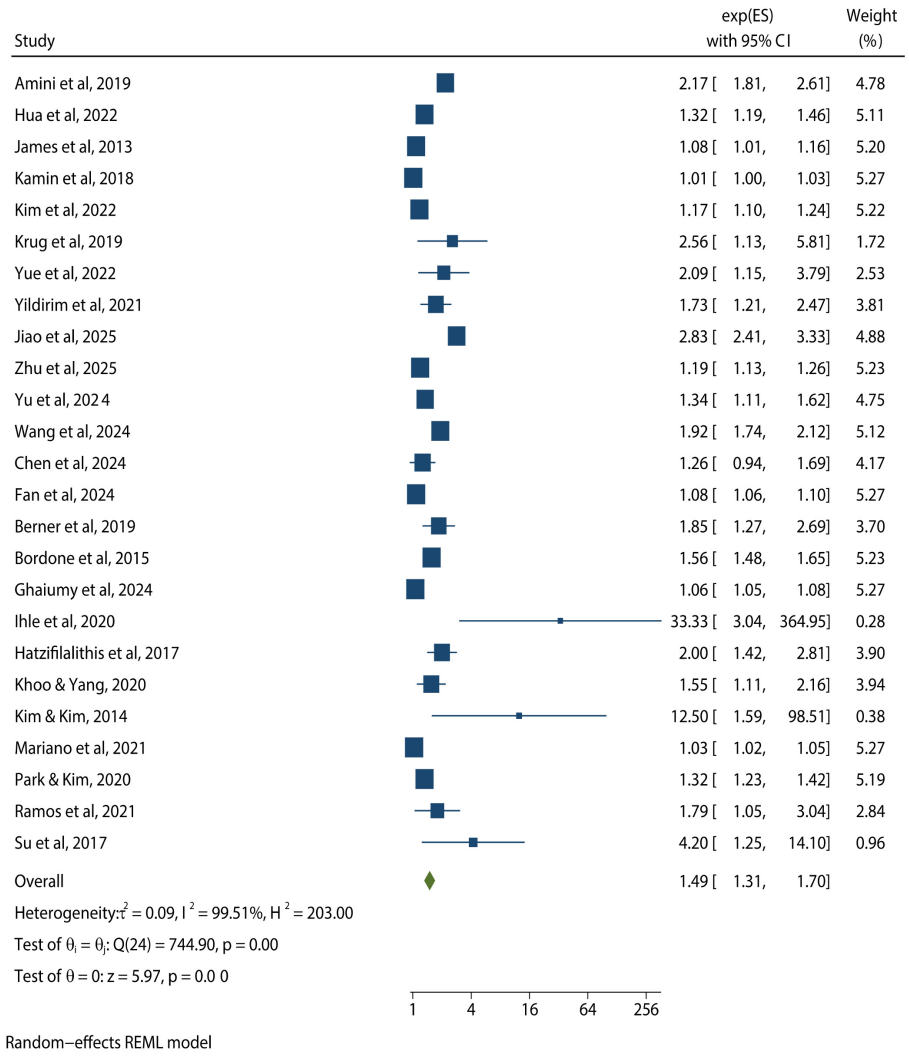

FIGURE 2
Forest plot summarizing pooled effect sizes from the meta-analysis of general internet use and cognitive function. All effect estimates are presented as pooled ORs with 95% CI, derived from a random-effects REML meta-analytic model. Squares correspond to single-study OR values; square size scales with each study's statistical weight. The pooled summary effect and its 95%CI are indicated by the diamond shape. Heterogeneity was evaluated via I^2 (I^2 = 99.51%) and Cochran's Q test ($P < 0.001$) and the overall pooled association was statistically significant ($z = 5.97$, $P < 0.001$).

potential outliers with extreme effect sizes—specifically, Ihle et al. (46) ($OR = 33.33$) and Kim and Kim. (41) ($OR = 12.50$)—to evaluate their impact on the overall results. After excluding Ihle et al. (46), the overall effect size was $OR = 1.48$ (95% CI: 1.30–1.68), which remained identical after excluding Kim and Kim. When both studies were removed simultaneously, the overall effect size was $OR = 1.46$ (95% CI: 1.29–1.67). These findings showed no statistically significant difference from the original overall effect size ($OR = 1.49$, 95% CI: 1.31–1.70). Hatzifilalithis et al. (49) had the smallest sample size ($n = 44$) among all included studies, while Kamin et al. (43) had the largest ($n = 29{,}576$). Excluding Hatzifilalithis et al. (49) yielded an overall effect size of $OR = 1.47$ (95% CI: 1.29–1.68), and excluding Kamin et al. (43) resulted in an OR of 1.52 (95% CI: 1.33–1.74). These findings remained consistent with the original pooled OR. In all scenarios, the pooled effect sizes remained statistically significant and directionally consistent with the primary analysis, indicating that the overall findings were not unduly influenced by any single study or by variations in sample size.

We further performed a sensitivity analysis stratified by the source of effect-size estimates (Table 2), to explore whether heterogeneity might stem from conversion of summary statistics. When restricted only to studies reporting original, unconverted ORs (Model 1, $n = 8$ studies), the pooled OR was 1.88 (95% CI: 1.50–2.37, $I^2 = 87.6\%$). For studies where effect sizes were converted from β, r, or raw regression coefficients (Model 2, $n = 16$ studies), the pooled OR was 1.25 (95% CI: 1.18–1.33, $I^2 = 96.9\%$). This difference in magnitude suggests that the method used to derive effect sizes may contribute to between-study heterogeneity. Still, the positive association remained statistically significant in both subgroups. Notwithstanding the consistent direction of point estimates after outlier removal, extreme residual heterogeneity persisted across all sensitivity models. This observation implies that neither outlying studies, extreme sample sizes, nor differences

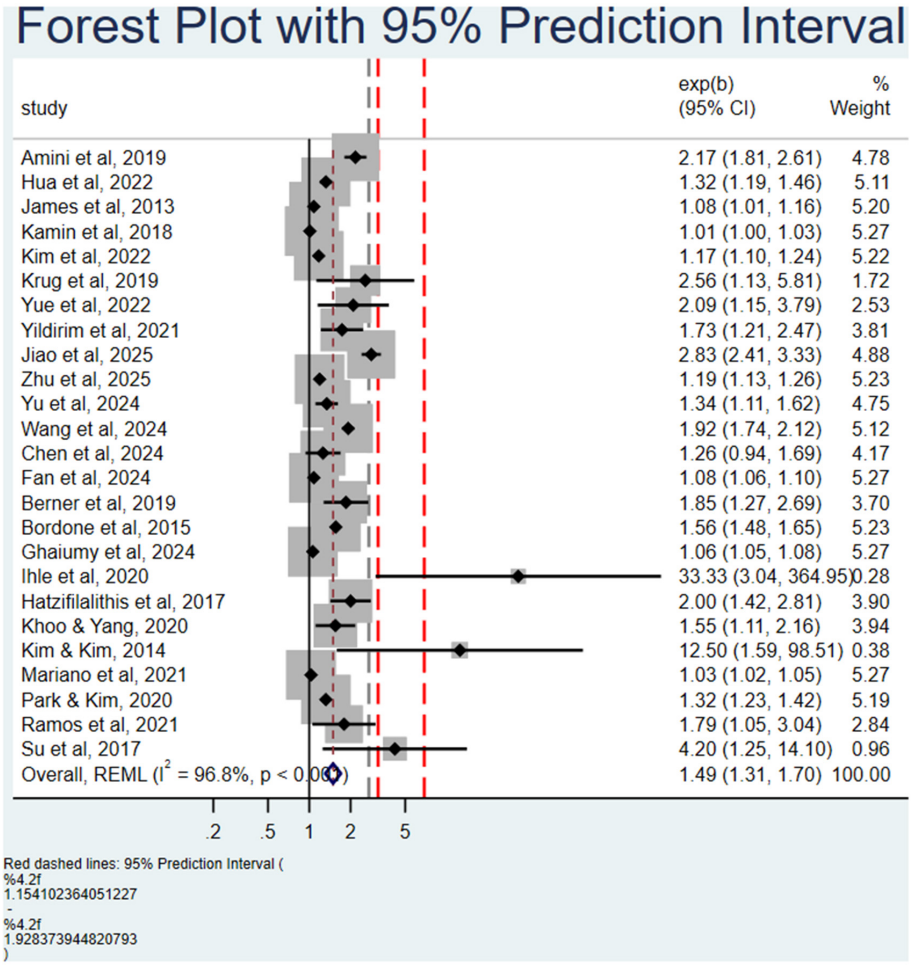

FIGURE 3
Forest plot of the pooled odds ratio with 95% prediction interval based on REML random-effects model. The 95% prediction interval was 1.15 – 1.93. Red dashed lines represent the 95% prediction interval. (I^2=96.8%).

in effect-size derivation fully explain the high between-study heterogeneity. Thus, all pooled estimates from these sensitivity analyses should be interpreted with caution.

3.7 Assessment of bias

Assessment of bias is summarized in Supplementary Table S3; The quality of the included studies was assessed using the National Institutes of Health Study Quality Assessment Tool. This instrument was selected for its operational simplicity and versatility, allowing for a standardized evaluation across both cross-sectional and cohort study designs. The assessment focused on potential bias originating from selection, information, measurement, and confounding. Based on the level of bias risk, the quality of each study was categorized into one of three ratings: "Good," "Fair," or "Poor," with a higher risk of bias corresponding to a lower quality rating. The quality determination was strictly based on the evidence explicitly provided within the included literature; no assumptions were made, adhering to a principle where unreported items were considered absent. Based on the assessment, 23 studies were identified as having a low risk of bias and were rated as "Good," while seven studies were classified as having a moderate risk of bias, receiving a rating of "Fair" (26, 30, 35, 38, 41, 43, 46). Only one study was found to have a high risk of bias and was consequently rated as "Poor" (22). The detailed risk of bias assessments are visualized in the summary plot (Figure 6) and matrix plot (Figure 7). We performed sensitivity analysis by excluding this single "Poor"-rated study to test the robustness of pooled estimates. The pooled effect size remained materially unchanged, indicating that the overall findings were not driven by this high-bias study (Figure 8).

As illustrated in Figure 9, publication bias was assessed using a funnel plot and Egger's regression test for the 25 studies included in the meta-analysis. The funnel plot exhibited visible asymmetry, which was confirmed to be statistically significant by Egger's test (Bias Coef. $=$ 4.79, $P < 0.001$). Furthermore, the Trim-and-Fill method was employed as a sensitivity analysis to assess the robustness of our findings against potential publication bias. Given that funnel plot asymmetry may also stem from substantial heterogeneity rather than solely from missing studies, the imputed results should be interpreted as exploratory. Based on the linear estimator, 13 hypothetical studies were added, yielding an adjusted

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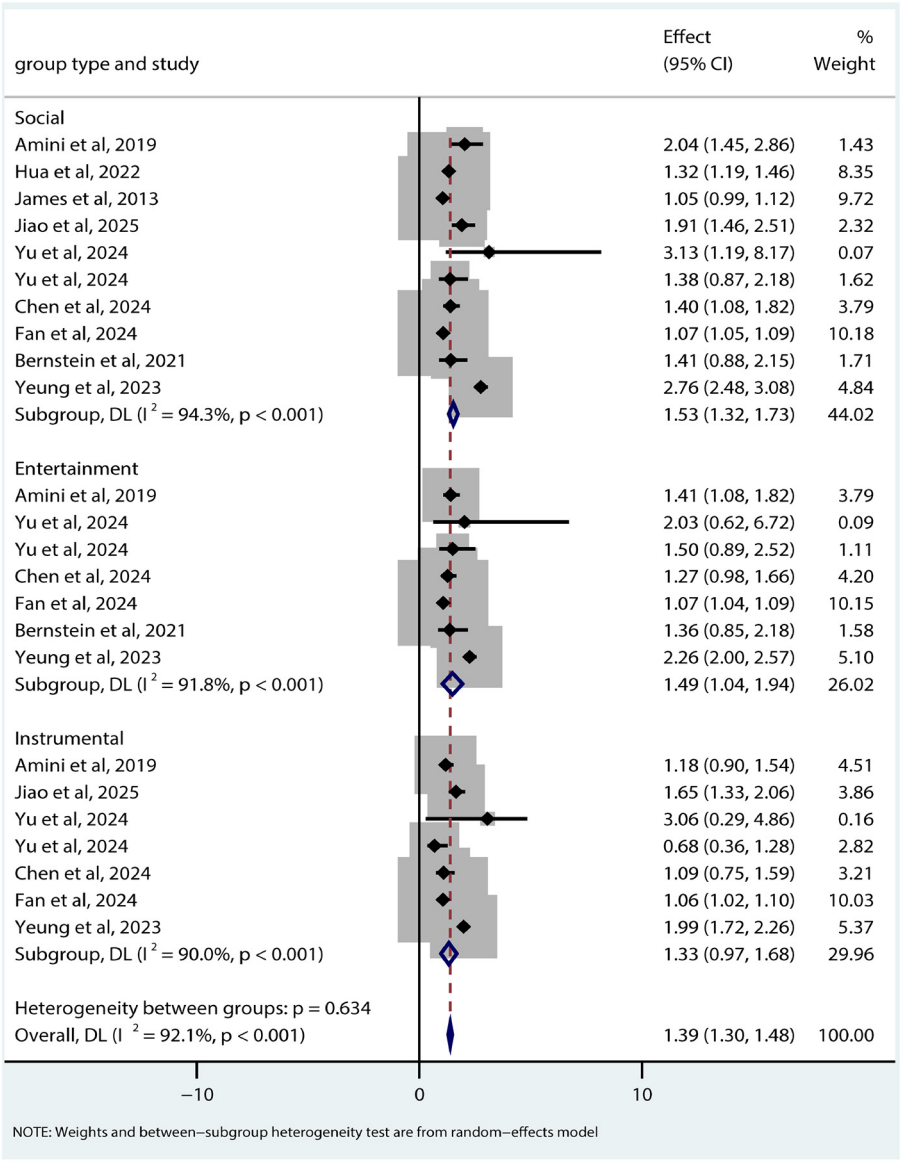

FIGURE 4
Subgroup analysis of the association between internet usage types and cognitive outcomes among the older adults. ES refers to the OR. The diamond markers represent the pooled effect estimates for each subgroup and the overall analysis. The horizontal lines represent the 95% CI.

pooled effect size of 1.107 (95% CI: 1.038–1.181). This suggests that while the association remains significant, the original estimate might have been slightly overestimated.

4 Discussions

Our meta-analysis, which synthesized data from 25 of the 31 included studies, yielded a pooled OR of 1.49 (95% CI: 1.31–1.70) under a random-effects model. This meta-analysis confirms a significant positive link between internet use and cognitive health. Although we must interpret these findings with caution due to the predominance of cross-sectional designs, the observed association is consistent with the notion that maintaining digital engagement could be a marker of cognitive reserve or may correlate with slower cognitive decline. While the pooled effect size of 1.49 represents a modest association, the magnitude of this observed association is broadly similar to associations reported for other well-documented correlates of cognitive function in older adults. For instance, Li et al. (58) reported that frequent intellectual activities were associated with an OR of 1.85 (95% CI: 1.30–2.63), and offline social activities yielded an OR of 1.27 (95% CI: 1.05–1.54). Similarly, higher community integration scores have been linked to better cognitive outcomes, with an OR of 1.22 (95% CI: 1.03–1.46) (53). While these findings demonstrate internet usage shows associations comparable in magnitude to those reported for traditional offline activities, the magnitude of this observed association remains relatively modest when placed in the broader context of digital technology research. Specifically, our pooled OR of 1.49 is lower than the robust

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TABLE 1 Results of meta-regression analyses exploring sources of between-study heterogeneity.

Effect	Estimate	*SE*	95% CI		*Z*-value	*P*
			LL	UL		
Model 1: methodological study characteristics						
Study design	−0.11	0.17	−0.46	0.25	−0.62	0.54
Confounder adjustment	0.04	0.18	−0.34	0.42	0.22	0.83
Model 1 test: $F_{(2,\ 22)} = 0.19$, $P = 0.82$						
Model 2: contextual characteristics						
Sample size	−0.17	0.18	−0.54	0.20	−0.93	0.36
Country income level	−0.11	0.16	−0.44	0.27	−0.66	0.52
Model 2 test: $F_{(2,\ 22)} = 0.74$, $P = 0.49$						

Model 1 examined methodological characteristics (study design and control for confounders). Model 2 examined contextual characteristics (sample size and country income level). LL, lower limit; UL, upper limit; CI, confidence interval; SE, standard error.

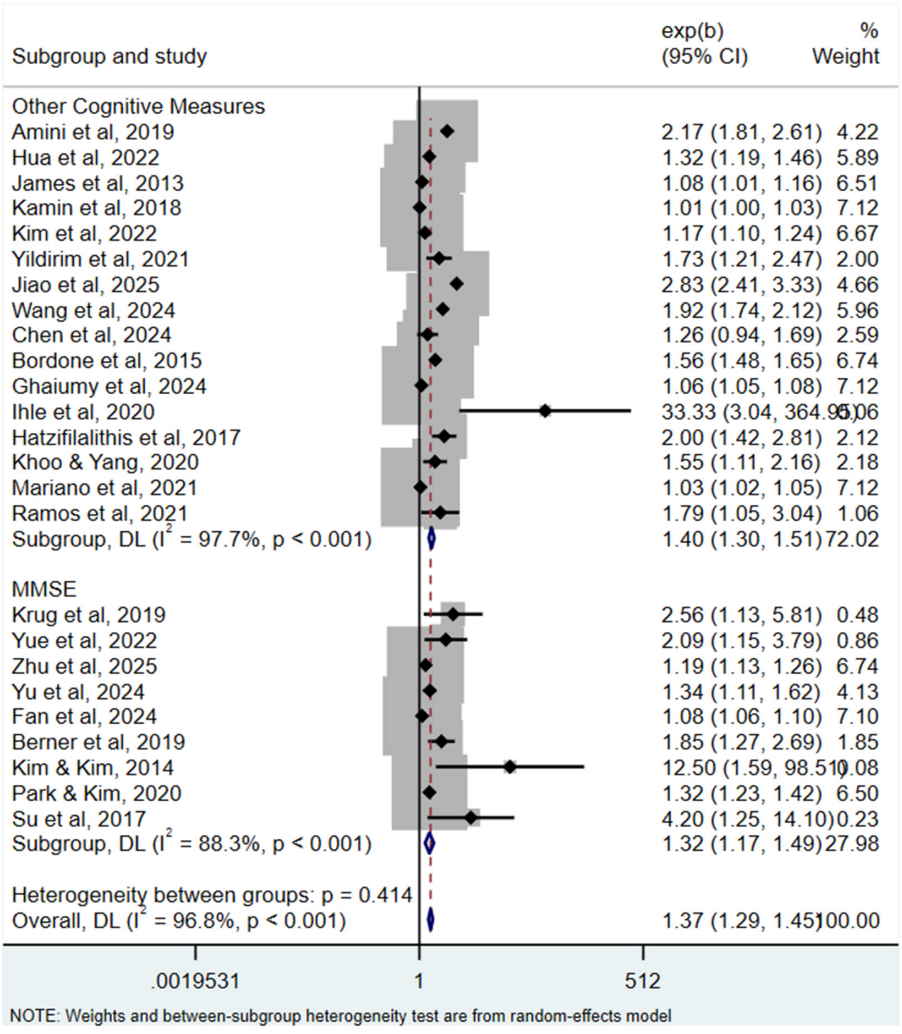

FIGURE 5
Forest plot of subgroup analysis stratified by cognitive assessment tool. The analysis compares the pooled effect estimates between studies using the Mini-Mental State Examination (MMSE) and those using other domain-specific cognitive measures. The diamond markers represent the pooled odds ratios (OR) with 95% confidence intervals (CI) for each subgroup and the overall estimate. The test for subgroup differences indicates no statistically significant difference between the two groups ($P_{between-group} = 0.414$). Weights are derived from a random-effects model (Der Simonian-Laird method).

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TABLE 2 Summary of sensitivity analyses by data source type.

Analysis model	Included studies (*n*)	Pooled OR (95% CI)	*P*-value	Heterogeneity (I^2)
Main analysis (All data)	25	1.49 (1.31–1.70)	<0.001	99.5%
Model 1: original ORs only	8	1.88 (1.50–2.37)	<0.001	87.6%
Model 2: converted metrics (β, r, b)	16	1.25 (1.18–1.33)	<0.001	96.9%

Model 1 included only studies reporting original Odds Ratios without data conversion. Model 3 included only studies with effect sizes converted from β, r, or unstandardized regression coefficients (b). OR, Odds Ratio; CI, Confidence Interval.

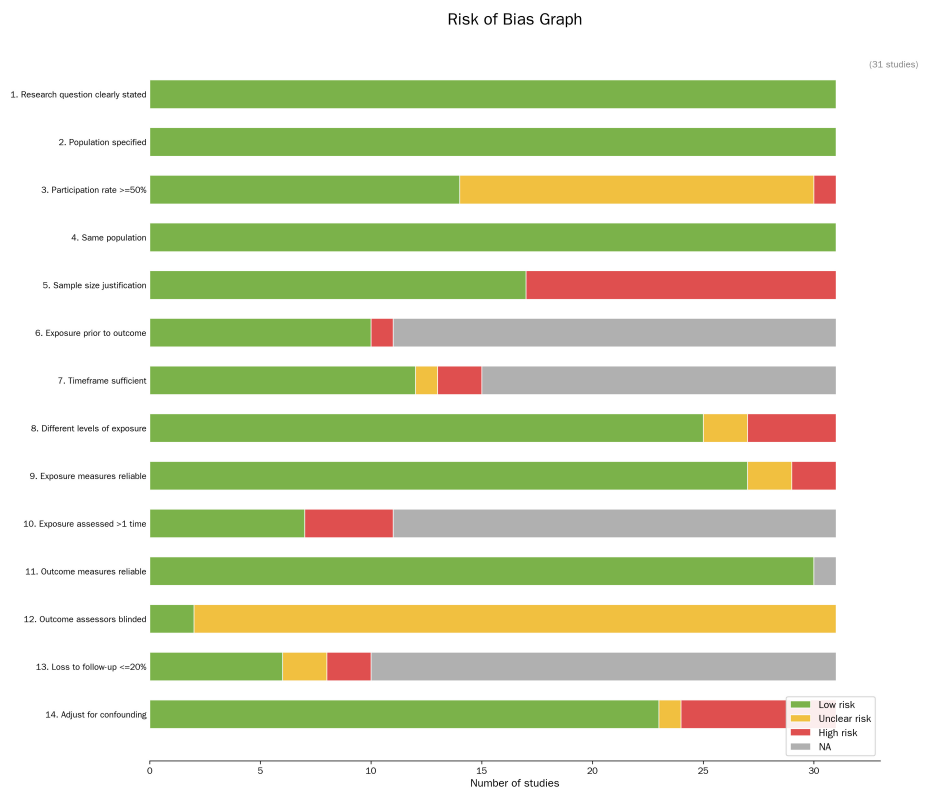

FIGURE 6
Risk of bias summary graph. The bar chart illustrates the proportion of the 31 included studies judged to be at low, unclear, or high risk of bias for each of the 14 quality assessment criteria based on the NIH tool. Green bars indicate low risk, yellow indicates unclear risk, red indicates high risk, and gray indicates not applicable (NA).

association reported in a recent comprehensive meta-analysis by Benge and Scullin (13), which observed an OR of approximately 2.38 (converted from their reported $OR = 0.42$) for general digital technology use among older adults. Varied operational definitions of digital exposure largely account for the observed between-study discrepancy. Benge and Scullin (13) incorporated diverse forms of digital participation (computers, mobile phones and combined multi-tool usage), while our meta-analysis exclusively focused on internet-specific behaviors. Their subgroup analysis further indicated that concurrent multi-device use linked to the strongest inverse association with cognitive decline ($OR = 0.25$), supporting a cumulative-benefit hypothesis: heterogeneous digital interaction may correlate with more intensive cognitive stimulation than single-purpose internet browsing. Our smaller pooled association may also stem from reduced susceptibility to pervasive healthy-user bias inherent to multi-device research designs. By isolating general internet use as the core exposure variable, the present findings precisely quantify its observed cognitive correlates and separate these associations from the exaggerated magnitude of associations observed in comprehensive multi-domain digital engagement.

We further explored potential sources of between-study heterogeneity via pre-specified multivariable meta-regression and a dedicated subgroup analysis stratified by cognitive assessment instrument. None of the examined study-level characteristics, including study design, confounder adjustment, sample size, national income level, or type of cognitive measurement tool, emerged as significant moderators. The subgroup comparison between studies adopting the MMSE and those using alternative cognitive tests showed comparable pooled associations, indicating that the observed link between internet use and cognitive function was not merely an artifact of the cognitive assessment method applied.

The absence of statistically significant moderation suggests that these methodological and contextual study features cannot fully



FIGURE 7
Risk of bias matrix by individual study. This heatmap displays the specific risk of bias rating for each included study across all assessment domains. Each row represents a single study, and each column represents a quality criterion. The color coding corresponds to the risk levels defined in Figure 6.

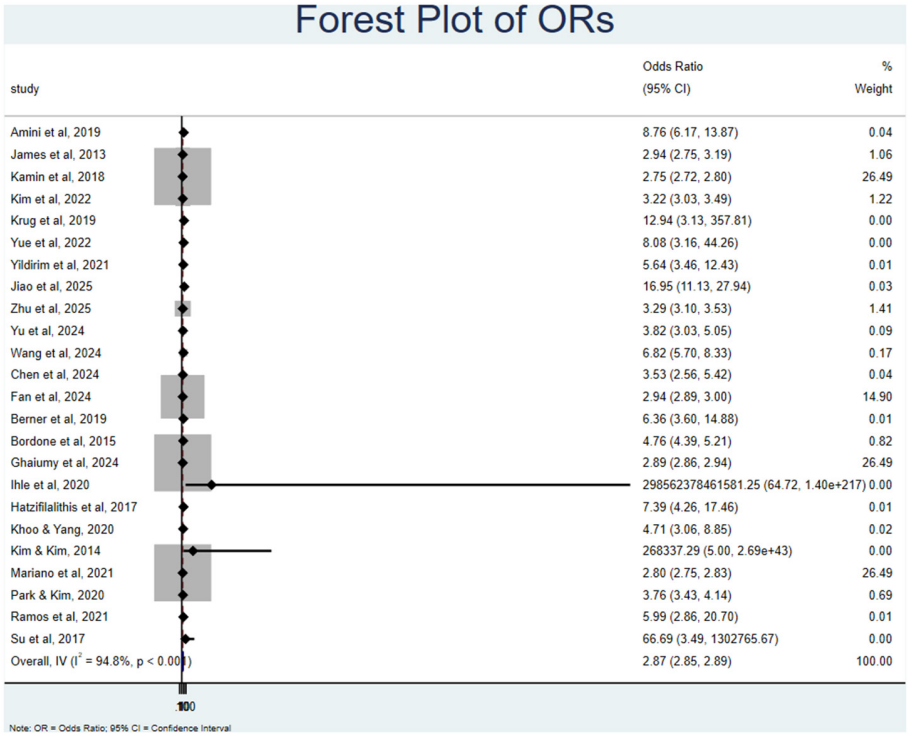

FIGURE 8
Forest plot of the sensitivity analysis excluding the study with high risk of bias. This analysis was conducted to test the robustness of the pooled estimates by removing the single study rated as "Poor" quality [Fan et al. (29)]. The squares represent the odds ratios (OR) for individual studies, sized according to their weight in the random-effects model. The diamond at the bottom indicates the new overall pooled estimate ($OR = 2.87$, 95% CI: 2.85–2.89). Despite the exclusion, substantial heterogeneity remains ($I^2 = 94.8\%$, $p < 0.001$), suggesting that the variability is not solely driven by this high-bias study.

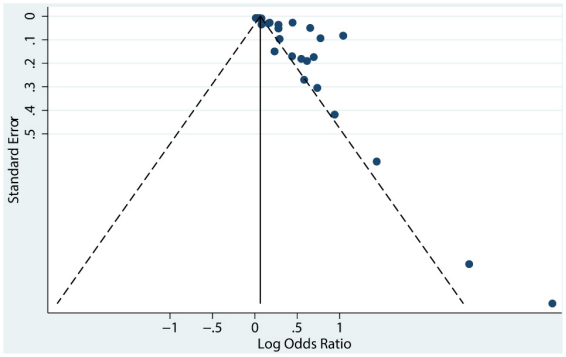

FIGURE 9
Funnel plot for the assessment of publication bias. The funnel plot displays the distribution of studies based on their effect size (Log Odds Ratio) against their precision (Standard Error). The pseudo 95% confidence limits are shown as dashed lines. Symmetry around the central vertical line suggests low risk of publication bias, while asymmetry may indicate potential bias due to selective reporting of significant results.

account for the substantial between-study heterogeneity identified in the primary analysis. This pattern implies that the heterogeneity may instead arise from unmeasured or underreported factors at the individual-participant level, such as the frequency and content of internet use, baseline cognitive status, education attainment, and lifestyle covariates that were inconsistently captured across original studies.

Notably, the consistent direction of association across all examined strata reinforces the robustness of our main finding: internet use remains positively associated with better cognitive outcomes regardless of these study-level characteristics. Even so, the high residual heterogeneity within subgroups highlights that other unexamined factors are the primary drivers of variation in effect sizes across the included literature.

Additionally, our sensitivity analysis stratified by effect-size derivation suggested that methods used to calculate ORs (original reported estimates vs. values converted from correlation or regression coefficients) may partially contribute to the observed heterogeneity.

Although our meta-analysis revealed a significant positive association between internet use and cognitive function, caution is warranted when interpreting the magnitude of this association. Egger's test indicated significant funnel plot asymmetry ($P < 0.001$), suggesting the potential presence of publication bias or small-study effects. To evaluate the potential impact of this bias, we conducted a trim-and-fill analysis. While this method imputed 13 potentially missing studies and the pooled OR decreased from 1.49 to 1.107 (95% CI: 1.038–1.181) after adjustment, this notable attenuation suggests that the original pooled estimate might have been somewhat overestimated. Therefore, the results of the trim-and-fill analysis should be primarily interpreted as a sensitivity analysis to delineate the possible range of the effect size, rather than as a definitive correction for publication bias. Notably, even after accounting for these potential missing studies, the adjusted confidence interval remained statistically significant (excluding the null value of 1). This further supports the relative robustness of the conclusion that a positive association exists, albeit the true effect size may be more modest than the initial estimate.

Meta-regression analysis examining specific patterns of internet usage revealed positive associations across different behavioral domains, including social, recreational, and instrumental use. Although social internet use exhibited a numerically higher pooled association, the meta-regression indicated no statistically significant differences among the subgroups ($P = 0.63$). Crucially, this absence of statistical significance should not be interpreted as evidence of equivalence across usage modes. Rather, it likely reflects inherent methodological constraints. First, with limited degrees of freedom ($df = 24$), the analysis may have been underpowered to detect subtle between-group variations, increasing the risk of a Type II error. Second, the categorization of internet use in observational studies is often prone to measurement overlap; broad definitions or composite scores in primary studies may not strictly isolate specific behaviors (e.g., passive browsing vs. active social networking), thereby introducing noise that dilutes potential contrasts. Consequently, substantial residual heterogeneity remained within categories, suggesting that the current classification of usage patterns may be too coarse to capture specific nuances. Nevertheless, sensitivity analyses corroborated the stability of these findings; even after excluding studies with small sample sizes or lower methodological quality, the subgroup differences remained non-significant ($P > 0.05$). This suggests that the comparable magnitudes of association observed are unlikely to be solely artifacts of outlier data or low-quality evidence, but rather point to a consistent underlying pattern where diverse digital behaviors are similarly linked to cognitive function in older adults, warranting more granular assessments in future research.

The lack of significant difference among internet use types aligns with the core tenets of Cognitive Reserve Theory. As proposed by Stern and Yaakov, cognitive reserve reflects the brain's active adaptation and flexibility ('software') rather than passive anatomical capacity (54). Our findings suggest that the act of engaging with the digital environment—regardless of specific content—stimulates this adaptive network efficiency. Furthermore, recent evidence indicates that high cognitive reserve protects the aging brain by maintaining efficient processing modes and delaying the need for compensatory mechanisms (55). Therefore, diverse online activities may collectively correlate with this adaptive baseline, making the specific behavioral domain less critical than the sustained cognitive engagement itself.

Furthermore, the socioemotional selectivity theory (SST) suggests that emotional regulation is vital for cognitive health. As proposed by Carstensen et al. (56), older adults prioritize emotion regulation over information seeking due to a perceived limitation in future time. Consequently, recreational and social internet use—while potentially less cognitively demanding than information searching—fulfill crucial emotional goals by maximizing positive affect and reducing loneliness or depression. This active preference for positive stimuli serves as a buffer against cognitive decline; by mitigating these psychosocial risk factors (57), such activities provide an alternative pathway to preserving cognitive function, leading to a comparable net benefit.

Our findings highlight robust associations between diverse internet-use patterns and cognitive performance across both cross-sectional and longitudinal designs. While these observational data do not yet substantiate direct public health interventions, they provide a critical empirical foundation for future research. Specifically, these results can inform the design of targeted longitudinal cohorts and randomized controlled trials to rigorously evaluate the causal impact of digital engagement on cognitive aging.

While our meta-analysis establishes a robust positive link between internet use and cognitive preservation, interpreting this association necessitates a nuanced perspective that transcends simple causality to account for underlying complexities such as reverse causation and residual confounding. Specifically, reverse causation may stem not only from differences in baseline cognitive capacity but also from the moderating role of cognitive reserve in selecting digital activities. Individuals with higher cognitive reserve tend to choose online activities with greater cognitive challenges, and it is this 'high-quality use' that likely serves as the potential neuroprotective factor. Conversely, early cognitive decline may lead individuals to actively avoid new technologies due to reduced self-efficacy, making 'non-use' a potential behavioral marker of preclinical cognitive deterioration. Furthermore, the role of confounding factors is not merely linear interference but reflects cumulative advantages over the life course. Education and socioeconomic status (SES) do not just serve as statistical covariates; they shape brain structure early in life. Additionally, sensory function (vision and hearing), a critical and often unmeasured confounder, likely determines both the ability to access digital tools and cognitive performance simultaneously. Finally, existing studies often treat internet use as a homogeneous variable, overlooking the heterogeneity of activity types. Future research needs to shift focus from mere 'access' to 'content' analysis and employ more causally robust designs (such as randomized intervention trials) to isolate the net effect of internet use on cognitive trajectories. The inconsistency in covariate adjustment across included studies poses a significant challenge to the validity of the pooled estimates. While some studies rigorously controlled for critical confounders such as baseline cognitive function and depressive symptoms, others relied solely on basic demographic adjustments. Furthermore, this methodological heterogeneity implies that the observed associations in less adjusted models may be driven by residual confounding rather than a true causal effect of internet use. Consequently, our meta-analytic results might partly reflect pre-existing health advantages or socioeconomic status, potentially leading to an overestimation of the protective benefits of internet engagement.

4.1 Limitations

Several limitations of this meta-analysis should be acknowledged when interpreting the findings: (1) substantial heterogeneity among primary studies remained unexplained, as subgroup analyses lacked sufficient statistical power to identify significant moderators, suggesting that true effects might be obscured by the limited sample size; (2) the reliance on ORs as the primary effect size metric may not fully capture the complex, continuous nature of cognitive function, and the necessary conversion of various statistics into ORs could introduce estimation errors; (3) the exclusion of gray literature, combined with significant funnel plot asymmetry, indicates potential publication bias, implying that the observed association—while statistically significant—may be overestimated and represents a more modest protective effect in reality; (4) the included studies lacked granular data on internet usage patterns (e.g., duration, frequency, or addictive behaviors), which prevented a dose-response analysis to clarify how different intensities of usage impact cognition; (5) potential reverse causation and residual confounding remain a concern, as the observed link may partly reflect a "digital divide" where cognitively healthier and wealthier seniors are simply more likely to be online, rather than a direct causal benefit of internet use itself; (6) the operational definitions of internet use varied substantially across included studies, ranging from simple binary indicators of access to complex measures of specific online activities; this lack of standardization in exposure assessment likely contributed to the observed heterogeneity and limits the comparability of findings across different research contexts. (7) the inability to conduct subgroup analyses by specific cognitive domains (e.g., memory, executive function) due to the predominant reporting of composite cognitive scores in primary studies, which precluded a detailed examination of how internet use differentially affects distinct aspects of cognition.

5 Conclusions

This meta-analysis synthesizes observational evidence on internet use and cognitive function in older adults. Data from 25 of the 31 included studies show internet use in older adults was associated with better cognitive outcomes across multiple usage patterns, including social, entertainment, and instrumental internet-use subtypes, although the evidence is highly heterogeneous and largely observational. Substantial heterogeneity indicates that the magnitude of this association varies by contextual factors. While the prediction interval points to a positive association overall, the wide range highlights considerable variability in effect size. Caution is warranted when generalizing these findings. These findings support further longitudinal and interventional research to determine whether and how digital engagement may contribute to healthy cognitive aging. Future studies should adopt standardized assessment metrics for internet use and cognition, with longer follow-up and diverse populations to explore the mechanisms of this association.

Author contributions

SW: Writing – original draft, Data curation, Formal analysis, Methodology, Conceptualization. YJ: Writing – review & editing, Project administration, Supervision. XB: Writing – original draft, Formal analysis, Methodology. MZ: Data curation, Methodology, Writing – original draft. HC: Writing – original draft, Data

curation, Validation. JW: Writing – original draft, Investigation. LL: Formal analysis, Writing – original draft, Investigation. YW: Writing – original draft, Investigation, Formal analysis.

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Conflict of interest

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2026.1926200/full#supplementary-material

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