The Association Between Passive and Active Social Media Use and Social Connectedness Across the Lifespan: A Systematic Review and Meta-Analysis

by

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DISSERTATION ABSTRACT

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Title: The Association Between Passive and Active Social Media Use and Social Connectedness Across the Lifespan: A Systematic Review and Meta-Analysis

Social media use (SMU) can have detrimental effects on mental health. Despite consistent increases in SMU across all age groups over the last two decades, trends in use, reasons for use, and impacts of use differ significantly across developmental age groups. There is growing interest in social connectedness (SC) as a protective factor for vulnerable age groups and a potential benefit of SMU, yet a review of the current literature testing the relationship between SMU and SC remains understudied, particularly across both passive and active types of SMU. In addition to the SC construct, the present review includes related SC constructs such as belonging, social support, loneliness, and social capital. To the author's knowledge, the present study offers the first systematic review and meta-analysis of the association between passive and active SMU and SC constructs across key developmental age groups. 24 studies are included, and eight main analyses are conducted to assess the mean effect sizes of SC across all included studies in both passive and active domains. Additional moderation analyses are conducted to test the potential moderating effects of age group, gender, and SC constructs and subgroups were conducted to interpret results. Results revealed small negative associations between passive social media use (PSMU) and SC, and small positive associations between active social media use (ASMU) and SC. PSMU was associated with higher levels of loneliness, and ASMU was associated with higher levels of SC when loneliness constructs were excluded. Moderation analyses yielded mixed results. Age was not a significant moderating variable. Gender emerged as a significant moderator for the relationship between ASMU and SC, and studies with higher proportions of female participants had stronger associations. Construct type significantly moderated both PSMU and ASMU models, and subgroup analyses suggest that studies focusing on loneliness influence the strength of associations between P/ASMU and SC. Findings call for rigorous research to better evaluate the relationship between SMU types and SC, meta-analyses of participant-level data to mitigate underpowered analyses, as well as more in-depth analysis of ASMU behaviors.

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DEDICATION

This is dedicated to those who feel alone, and to those who have helped me feel connected. To my community, my friends, my family, and colleagues, those here today, and those here in spirit.

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CHAPTER I

INTRODUCTION

Social media (SM) is an increasingly integral component of modern life, with its use expanding substantially across diverse populations and age groups since 2005 (Perrin, 2015). Not surprisingly, youth are among the most active users of SM platforms. According to a Pew Research Center report, teens not only access these platforms frequently but also consider them essential for social connection and identity exploration (Park et al., 2025). Younger adolescents typically engage with SM daily, and the amount of time youth spend online increases with age (Nagata et al., 2025). Roughly 96% of youth ages 13-17 report daily internet use and engage with at least one SM platform a day (Park, 2025). Between 2014 and 2022, the percentage of youth who reported "constantly" using the internet increased from 24% to 46% (Park, 2025). Notably, general screen use has spiked in recent years. Between 2015 and 2021, screen time, which included social media use (SMU) and content creation, increased among youth ages 8 – 12 by an average of 8 minutes per day (Rideout et al., 2021). Between 2019 and 2021, time spent using screens among this age group increased more steeply by 42 minutes per day (Rideout et al., 2021). Similarly, SMU remains ubiquitous and deeply integrated into the daily life of young adults and emerging adults. This age group is more likely than any other to report regularly using multiple platforms for extended periods (Perrin, 2015). A 2015 Pew Research Center report found that by 2015, 90% of emerging adults aged 18-29 used SM daily (Perrin, 2015). In a study of 575 emerging adults (aged 18-25), Woodward et al. (2025) found that participants reported spending over 8 hours per day across each of their SM platforms. This high level of engagement reflects both the normative role of digital communication in emerging adulthood and its potential influence on mental health during a transitional and identity-forming life stage.

SMU among middle adults (30-64 years) is also high(Gottfried, 2024). Between 2005 and 2015, the percentage of American adults using SM sites increased from 7% to 65% (Perrin, 2015). The literature suggests that SMU for adults over 30 is predominantly used to maintain existing social relationships, access news or community information, and support professional and internet-based networking (Sidoti et al., 2024). For many adults, SM is the primary tool for maintaining communication and connection with family and friends, especially when physical distance or time constraints limit face-to-face interaction (Cotten et al., 2012). These users often report that platforms such as Facebook and Instagram help them stay socially connected, provide emotional support, and coordinate social activities or caregiving responsibilities (Ellison et al., 2007; Vitak, 2012). While many report SMU has enhanced their social well-being, outcomes vary based on relationship quality and platform engagement style (Ellison et al., 2007; Sheldon et al., 2021; Sidoti et al., 2024; Vitak, 2012). For example, emerging research has found that some adults in the Baby Boomer generation use and rely on SM sites to *compensate* for face-to-face interactions and other social activities (Sheldon et al., 2021). In a survey of 414 middle-aged adults, Sheldon et al. (2021) found that as life satisfaction increased, SMU decreased, although these findings were specific to users of Facebook and Instagram who primarily engaged in SMU for the purpose of social closeness or diversion.

SMU has also drastically increased among older adults (ages 65 and older) from just 2% of aging adults in 2005 to 35% in 2015 (Perrin, 2015). Despite maintaining lower rates of SMU than youth, older adults have shown steady increases in SM adoption over the last decade, with uptake accelerating during the COVID-19 pandemic (Cotten et al., 2022, 2023; Perrin, 2015). Uptake is higher among relatively younger seniors, those with better health, higher education, and greater income, and those with stronger digital skills, particularly for platforms such as

Facebook, X, and Instagram (Nie et al., 2024; Tsukada et al., 2024). The platforms older adults use often differ from those of younger users (e.g., Facebook and WhatsApp are common entry points), and, as with adults in the 30-64 bracket, the purpose of use is typically oriented toward maintaining family ties, receiving health information, and instrumental communication rather than trend-driven content creation. Several recent empirical studies and reviews find that SM can support social connection and self-care efficacy among older adults, particularly when use is purposeful (e.g., contacting family/friends, receiving support, or accessing health resources; Lin & Lachman, 2024; Nie et al., 2024). However, the effects are conditional on users' eHealth literacy and access to support for technology use (Lin & Lachman, 2024; Nie et al., 2024). Overall, the evidence suggests that older adults are engaging with SM platforms at a growing rate, which in turn expands opportunities for social connection and health communication, but the net impact on well-being depends on who uses these tools, how they are used, and whether older adult users possess the necessary digital skills and supports to capitalize on the potential benefits (Cotten et al., 2022; Lin & Lachman, 2024; Tsukada et al., 2024).

It is not surprising that both middle-aged and older adults use SM at lower rates than youth and young adults, who have had access to SM at significantly younger ages. However, these differences may shrink as subsequent generations replace the older adult population, and the trends of SMU among older adults are likely to increase. Additionally, current trends clearly indicate that adults of all ages are significantly increasing their SMU, and across all age groups, there is a trend of using SM to establish or maintain relationships and friendships. Given these commonalities across age groups, both in purpose and in increasing use, it is essential to critically examine the impact SMU has on social and mental health throughout the lifespan.

How Important are User Demographics?

One notable difference in SMU is found between females and males (Reyes et al., 2022). Several studies have found that females are more likely to seek out SM sites that support maintaining and communicating in existing relationships, provide social information, and viewing other people's photos, while males are more likely to seek out SM sites that support developing new relationships, information sharing and education, and online gaming (Barker, 2009; Hogue & Mills, 2019; Krasnova et al., 2017; Muscanell & Guadagno, 2012; Reyes et al., 2022). Although gender gaps in overall usage have shrunk over time, there is still a 6% difference in SMU between women (68%) and men (62%; Perrin, 2015).

Studies document persistent disparities in SMU, specifically, among older adults, individuals in racial and ethnic minority groups, people of lower socioeconomic status, and those with poorer health (Cotten et al., 2022; Nie et al., 2024). There are also significant differences in usage by education level and household income; individuals in higher-income households and higher levels of education are significantly more likely to use SM (Perrin, 2015). Specifically, older adults of minoritized status and poorer health are less likely to use SM or to derive the same benefits (e.g., accessing relevant health information, connecting with others), pointing to ongoing "digital inequality" that may limit SM's reach as a tool to reduce loneliness and isolation in later life (Cotten et al., 2022; Nie et al., 2024).

There are significant differences in platform-to-platform SMU across demographic groups. For example, apps such as LinkedIn and X appeal to individuals with annual household incomes of $100,000 or more, with nearly a third of users (29%) reporting these high earnings (Gottfried, 2024). Use of these apps is consistent with broader trends, emphasizing users of higher education and income. Conversely, 63% of teens in the United States (U.S.) use TikTok

and have an annual household income of $30,000 or less (Park et al., 2025). Despite an overall decrease in gender gaps for SMU, 51% of U.S. women report ever using Pinterest, compared to only 19% of U.S. males (Sidoti et al., 2024). In the U.S., there are no significant differences in SMU based on race or ethnicity when looking at all platforms combined(Perrin, 2015). For instance, in 2015, usage of SM was 65% White, 65% Hispanic/Latine, and 56% African American/Black (Perrin, 2015). However, Hispanic/Latine (58%) and Asian (57%) adults are more likely to use Instagram than White adults (43%; Gottfried, 2024). These platform-based differences demonstrate the importance of app-specific context and appeal, and highlight that some apps appeal to specific audiences, whether due to their design (e.g., TikTok, Vine) or their function (e.g., LinkedIn).

Broad differences in SMU by race, ethnicity, gender, income, and other sociodemographic variables simply do not apply to all SM sites. In fact, in many cases, age is the only demographic predictor of use that spans across multiple SM sites (Groves, 2024). For example, middle adults report using Facebook and YouTube, which consistently emerge as the most used platforms in this cohort (Gottfried, 2024). Roughly 78% of middle adults report ever using Facebook, and about 94% report ever using YouTube (Gottfried, 2024; Sidoti et al., 2024). In contrast, use of platforms such as Instagram, TikTok, Snapchat, and Pinterest tends to decline with age: adults aged 30-49 are substantially more likely to use Instagram (roughly 66%) than those aged 50-64 (Gottfried, 2024; Sidoti et al., 2024). Time spent on SM and engagement frequency also tend to be lower among older individuals within this age range. While the cohort of 30–49-year-olds reports using multiple platforms regularly, usage becomes less frequent and more selective as one moves toward the 50-64 year-old cohort (Smith & Anderson, 2018). As

this review establishes, despite cohort differences among younger and older middle adults (30-64 years), most SM studies do not differentiate usage patterns between these groups.

Considering the persistent relevance of age across SM platforms and SMU, the present review aims to evaluate outcomes among each age group (6-17 years, 18-29 years, 30-64 years, 65 years and older). Specifically, this review defines SMU, explores the negative and positive associations between passive and active SMU, and details the importance of social connectedness (SC), the outcome of interest.

Negative and Positive Implications of SMU

SMU is historically tied to negative mental health outcomes, including depression (Groves, 2024), anxiety and fear of missing out (Dhir et al., 2018; Hunt et al., 2018; Przybylski et al., 2013), loneliness (Hunt et al., 2018), envy and social comparison (Appel et al., 2016), body dissatisfaction and eating concerns (Fardouly et al., 2015; Filippone et al., 2022; Jiotsa et al., 2021)**,** stress and emotional exhaustion (Chen & Li, 2017), reduced self-esteem (Vogel et al., 2014), reduced life satisfaction (Verduyn et al., 2017), and suicidal ideation (Kowalski et al., 2019). Other negative outcomes can include sleep disturbances (Scott et al., 2019), compulsive SMU and impaired functioning (Dhir et al., 2018; Kuss & Griffiths, 2017), lower academic success, and victimization from cyberbullying (Braghieri et al., 2022; Hamm et al., 2015; Kowalski et al., 2019).

Many of these outcomes are found across various age groups. For example, one large (*n* = 3,826) youth-focused longitudinal cohort study using within-person repeated measures models found positive associations between increases in screen time and SMU and depressive symptoms over time (Boers et al., 2019). A national longitudinal cohort study of U.S. adolescents (*n* = 6596, ages 12-15 at wave 1) showed that greater daily time on SM prospectively predicted

higher odds of internalizing problems such as depression and anxiety, and comorbid internalizing and externalizing problems at a one-year follow-up (Riehm et al., 2019). A recent LifeStance Health survey of emerging and middle adults revealed negative outcomes to SMU included anxiety about politics (37%), information overload (27%), sleep disruption (22%), negative self-image or comparison to others (21%), fear of missing out (19%), and loneliness/isolation (19%; Villalobos, 2025). Although SMU and well-being among older adults is not well understood, cross-sectional research has found associations between depression and SMU among older adults (Cotten et al., 2022). Furthermore, while there are positive outcomes associated with SMU among younger users, such as improved social well-being, older adults may not infer these same benefits (Quinn, 2021). These discrepancies may be explained by a lack of familiarity and exposure to SM (i.e., technological literacy), as well as a lack of representation of older adults on SM networks (Quinn, 2021). Overall, despite many studies finding associations between SMU and negative outcomes (e.g., depression, reduced life satisfaction) for youth, adult, and older adult populations, new research suggests these associations may be more complicated, bidirectional, and dependent on other contextual factors than previously thought.

As SMU continues to grow, researchers are beginning to explore its positive impacts on mental health. These include improved psychological well-being and life-satisfaction (Best et al., 2014; Kim & Lee, 2011), identity exploration and self-expression (Manago et al., 2008; Michikyan et al., 2014), enhanced agency and empowerment, especially in marginalized groups (Bennett & Segerberg, 2012; Velasquez & LaRose, 2015), and reduced feelings of isolation, specifically among older adults (Chen & Schulz, 2016; Nef et al., 2013). Other beneficial outcomes include increased SC(Grieve et al., 2013; Janssen et al., 2025), enhanced perceived

social support (Nabi et al., 2013; Oh et al., 2014), enhanced sense of belonging and community (Trepte & Reinecke, 2013), emotional support and coping (Frison & Eggermont, 2016; Seabrook et al., 2016), and enhanced learning and cognitive stimulation (Ellison et al., 2014; Greenhow & Lewin, 2016).

In a longitudinal study of Finnish youth (n = 2,891, ages 13-19), no evidence was found that SMU predicted depressive symptoms (Puukko et al., 2020). On the contrary, depressive symptoms were found to predict small increases in active SMU, pointing to the bidirectional nature of SMU and negative outcomes (Puukko et al., 2020). Among emerging adults, a longitudinal study of undergraduate students tracked SMU and depressive symptoms across multiple waves, with results indicating no consistent prediction between SMU and later depression (Heffer et al., 2019). Researchers have found that among emerging and middle-aged adults, daily usage of SM to connect and respond to others online was positively associated with social well-being, positive mental health, and self-rated health (Bekalu et al., 2019). The same LifeStance Health survey found 52% of SM users experienced stronger connections with friends and family as a result of usage (Villalobos, 2025). Thirty-two percent of users found SMU connected them with other individuals who shared their experiences and could relate to their perspectives (Villalobos, 2025). Another 32% reported SM enhanced their ability to find people with shared interests, and 27% reported receiving access to support communities (Villalobos, 2025). Additional positive impacts reported included entertainment and humor (45%), stress relief and relaxation (31%), learning new perspectives (30%), educational opportunities (30%), and inspiration for hobbies and self-expression (25%). It is notable that of the outcomes listed on this survey, a greater percentage of participants endorsed positive outcomes compared to negative outcomes.

Although evidence is limited, a longitudinal study by Cotten et al. (2023) found that SMU did not predict depressive symptoms, nor did depressive symptoms predict SMU among older adults. Furthermore, the only major predictor for depression among the sample was pre-existing depression, and the major predictor for SMU was previous SMU (Cotten et al., 2023). Older adults may experience unique protective and risk factors regarding SMU. A literature review of 11 studies published between 2014 and 2020 found that overall, SMU among older adults can reduce loneliness and isolation, increase connections between loved ones, and facilitate feelings of belongingness and community (Kusumota et al., 2022). In a longitudinal study of Dutch older adults, Janssen et al. (2025) found that increased social internet use was negatively associated with loneliness over time. Together, these mixed results across age groups suggest that not only is SMU likely to have fewer negative impacts than previously believed, but that testing overall usage may not provide a sufficiently nuanced understanding of the relationship between SM and mental and social health. Researchers are beginning to explore SMU in greater depth, expanding beyond measurements of screen time or time spent on SM sites, to examine *how* users engage with SM.

What is Social Media?

The evolving nature of SM, ranging from simple blogging websites to live-streaming platforms, has contributed to inconsistent definitions of SM in both dictionaries and the scientific literature. Based on the definition provided by Merriam-Webster dictionary, online platforms must meet the following criteria to be considered a SM: (1) Provide electronic communication, and (2) Allow users to form communities to share the following: information, ideas, personal messages, and other content, such as videos (*SOCIAL MEDIA Definition & Meaning - Merriam-Webster*, n.d.).

The Cambridge Dictionary defines SM as "websites and computer programs that allow people to communicate and share information, opinions, pictures, videos, etc. on the internet, especially social networking websites" (*SOCIAL MEDIA Definition | Cambridge English Dictionary*, n.d.). Wikipedia defines SM as "technologies that facilitate the sharing and aggregation of content (such as ideas, interests, and other forms of expression) amongst virtual communities and networks." Wikipedia also provides definitions and examples of categories of SMs (Wikipedia, 2025). For example, sites focused on establishing social connections and networking for personal or professional reasons are referred to as social networking sites (Wikipedia, 2025). Media sharing networks, on the other hand, emphasize the posting, sharing, and reposting of images and videos (e.g., TikTok and Instagram; Wikipedia, 2025). Live streaming platforms, including Twitch and Facebook Live, emphasize real-time communication between the content creator and the content consumer (Wikipedia, 2025). There are also discussion and community forms (e.g., Reddit and Discord), as well as microblogging platforms (e.g., X and Mastodon; Wikipedia, 2025). Previous meta-reviews have leveraged the definition developed by Carr and Hayes (2015); SMs are "(a) internet-based, (b) allow asynchronous communication, (c) facilitate interaction between users, (d) provide value through user-generated content, and (e) enable simultaneous communication between multiple users" (Godard & Holtzman, 2024).

These definitions are broad and do not provide clarity on whether websites that are geared for one-way content consumption should be considered SM. YouTube, for example, does not have a function allowing users to create message boards or community spaces for other users to consume, create, or add their own posts. Platforms such as Reddit, on the other hand, allow individuals to create their own community board where anyone can post content, and anyone can

comment and reply to the original poster, in addition to upvoting ("liking") or downvoting ("disliking") the original post or subsequent comments. Arguably, this feature is a key factor in helping users "form communities." Furthermore, although individuals can comment on YouTube videos, there is no way to send direct messages to content creators or other users, nor to share YouTube videos in-app. YouTube and Podcasts serve similar purposes: they are content creation platforms where individuals can consume content, like or comment on other users' uploads, or create their own content. However, there are no options for users to contact other users or creators directly. A key distinction between YouTube and other audio content platforms (e.g., podcasts) is that YouTube also has features where content creators can post personal messages in text, create voting polls for users (e.g., "which UFC fighter is most likely to win the next event"), and users have distinct profiles that allow for creating playlists of other user's content, creating and uploading their own content, liking and commenting on videos, and following specific creators ("subscribing"). The ability to subscribe to specific "channels," groups, or individual creators on YouTube is arguably a way to form a community. Although YouTube is an example of a SM geared toward passive use, (e.g., no ability to form communal profiles or boards or to send direct messages) the ability for individuals to participate actively (e.g., liking videos, creating and posting their own content) and establish some form of community (e.g., commenting on videos, subscribing to the same channels as friends, etc.) suggests that YouTube meets the criteria for SM.

There are several SMs that clearly meet the dictionary definitions of SM, for example, TikTok, Instagram, Facebook, Vine, Snapchat, Discord, Reddit, etc.; SMs that clearly provide consumption, creation, sharing, *and* messaging options in-app. For the purposes of this review, there are clear distinctions between SM apps that allow for in-app communication and direct

messaging, and apps that are designed to replicate or replace other forms of direct communication. WhatsApp, for example, is designed to allow users to text, call, and video chat with other users. Functionally, there is no difference between apps such as WhatsApp and the text message or call function within every phone. Furthermore, these apps require users to already have access to other user information (i.e., phone number), so there is also no networking or community-forming feature within the app itself, a key criterion for SMs. This distinction is important, as there is a significant difference between texting or calling individuals with whom you must already have enough contact to have gained access to their phone number, and consuming the visual content curated by friends *or* strangers online, with no requirement for direct communication. This distinction is not solely based on predetermined definitions of SM or based on theory but is reflected in country-wide SMU legislation. According to the BBC, Australia's SM ban for youth explicitly bans traditional SM sites (e.g., Facebook, Instagram, Snapchat) in addition to YouTube and streaming platforms such as Twitch (Livingstone, 2026). WhatsApp, however, is not included in this ban, nor is YouTube Kids, as neither of these platforms allows posting or commenting by individual users (i.e., children using the app), or enables or promotes communication between multiple other users (Livingstone, 2026). Therefore, it is notable that other meta-analytic reviews of SMU do not always distinguish between these platforms, leading to a problematic lack of nuance and conflation of associations between SMU platforms, non-SMU apps, and mental or social health outcomes (e.g., Marciano et al., 2024).

Other online spaces mimic SMs, but do not ultimately meet all the requirements for the definition. For example, Yahoo Answers and Quora are both sites where individuals can post personal questions and other users can respond with answers, advice, or suggestions. These sites,

although similar to Reddit in allowing posts and replies, do not support continued interaction between users, either through community board spaces or direct messaging options. Therefore, these websites do not meet the criteria for community forming. Yelp and other review sites are also not SMs, as these are not functionally designed to promote or sustain direct communication, community, or connections. Carr and Hayes (2015) include websites such as Yelp within their definition of SMs, and as such, meta-analyses that have relied exclusively on Carr and Hayes' (2015) definition of SM sites risk missing nuance due to overly broad definitions (e.g., Godard & Holtzman, 2024). On the other hand, websites that allow for anonymity may still be considered SMs. For example, 4chan is an anonymous SM akin to Reddit. Users can post, like, and comment within specific community boards. Although there are no direct messaging features, and although members post anonymously, websites such as 4chan can promote a sense of community, as users, for better or worse, can form a community by sharing opinions and ideas without the social repercussions of personal identification.

Passive Versus Active Social Media Use

Scholars increasingly distinguish between two primary types of SMU: passive and active. Passive social media use (PSMU) refers to scrolling through posts, viewing content, or observing others without direct interaction (Verduyn et al., 2017). Passive users do not post their own content or interact publicly (e.g., commenting on posts) or privately (e.g., direct messaging) with other users. On the other hand, active social media use (ASMU) involves posting, commenting, messaging, and other forms of interactive engagement (Verduyn et al., 2017). Understanding usage patterns among youth, young adults, middle-adults, and older adults is critical, as both PSMU and ASMU appear to have different psychological implications. Verduyn et al. (2017) suggest that PSMU tends to promote negative emotional outcomes such as increased depressive

symptoms and loneliness. PSMU is also associated with increased social comparison, particularly among adolescents, and reduced social reciprocity (Cheng et al., 2023; Lewin et al., 2023). In contrast, research finds mixed effects for active users. Some studies found that SMU not only enhanced peer support, social capital, and identity exploration, but these findings were particularly supported among active users (Memon et al., 2018; Shannon et al., 2022). Other studies suggest ASMU enhances social connection and perceived support (Verduyn et al., 2017), although these associations may be mediated by mechanisms such as self-esteem, fear of missing out, and online social comparison (Orben, 2020). Orben (2020) argues that individual differences and contextual factors often moderate these effects, and cautions against overly simplistic conclusions. Additionally, PSMU and ASMU often lack consistency in operationalization, which contributes to mixed findings in empirical studies (Orben, 2020). Overall, despite an expanding body of research, the literature remains fragmented, with inconsistent definitions and measurements of PSMU and ASMU, as well as SC.

Social Connectedness and Loneliness

SC is a key aspect of mental health. For youth, high levels of SC, including strong bonds with family, peers, and community, act as protective factors that reduce mental health challenges such as depression and anxiety (Birrell et al., 2025; Blum et al., 2022). Conversely, low SC contributes to immediate and long-term mental health issues, highlighting the importance of fostering supportive social environments for young people (Blum et al., 2022; Grigorian, 2025). SC is consistently associated with lower risks of depression and anxiety among adults; longitudinal studies show that social support and having larger social networks protect against adverse mental health outcomes in varied populations, supporting efforts to identify adults at risk due to low connectedness or loneliness (Wickramaratne et al., 2022). In older adult samples,

research demonstrates that improved SC is linked to lower risks of chronic illness, depression, and premature death, and that fostering social networks can promote healthy aging and mitigate loneliness (Simionato et al., 2023). Naturally, the relationship between SC and mental health is reciprocal, as some individuals experiencing mental health conditions may find it more challenging to develop, improve, or maintain SC (Schwartz & Litwin, 2019).

As previously mentioned, there are important considerations for evidence synthesis on this topic, as PSMU, ASMU, and outcome variables such as SC are inconsistently operationalized across studies. SC, in particular, is regularly operationalized using measurements of loneliness (Kelley et al., 2025). This is, in part, due to previous research on SC, which has utilized an abundance of terms to define and describe SC, including "social relationships, social cohesion, social support, social networks, social belonging, and the deficit side of the equation, social isolation and loneliness" (Jordan, 2023). As Jordan (2023) revealed, several quantitative studies have demonstrated common qualifiers for SC, including "feelings of belonging, being understood and accepted by group members, and a sense of solidarity within a group." It is important to note that while social belonging and SC are distinct constructs, belongingness is cited as a key aspect of SC (van Bel et al., 2009). Haslam et al. (2015) defined SC as "the sense of belonging and subjective psychological bond that people feel in relation to individuals and groups of others." Previous systematic reviews have utilized this definition to guide the selection of studies and their included measures of SC (Plackett et al., 2024). Further, while loneliness can be considered a separate construct from SC, a scientific expert in loneliness, Jeremy Nobel, , states that "Loneliness is a gap between the social connections we have and the ones we want to have" (Cambieri, 2024). This appraisal of loneliness is reflected in previous studies of SC, including Plackett et al.'s (2024) article, "Measures of Social Connectedness Among Adult

Populations: A Systematic Review." Of the ten articles included in this article, six used measures of loneliness, including the UCLA Loneliness Scale (Russell, 1996) and the De Jong Gierveld Loneliness Scale (de Jong-Gierveld & Kamphuls, 1985). This perspective on SC and loneliness is consistently reflected in the operationalization and measurement of SC in previous studies.

Recent psychometric analyses, such as the 2025 evaluation of the Social Connectedness Instrument (SCI), highlight that most widely used instruments to measure loneliness—such as the UCLA Loneliness Scale—focus on the perceived intensity of disconnection, mapping loneliness as the negative end of a connectedness continuum (Kelley et al., 2025). This perspective aligns with theoretical models that position loneliness and SC as opposite poles: high loneliness signifies low connectedness, and vice versa (Holt-Lunstad, 2024). Research suggests that individualized interventions targeting specific psychosocial or psych-emotional factors—identified as latent constructs in the SCI—can more effectively foster social connection, while also confirming that measures of loneliness robustly capture the subjective, central experience of low SC (Holt-Lunstad, 2024; Kelley et al., 2025).

Peer-reviewed studies consistently demonstrate that the use of loneliness measures, such as the UCLA Loneliness Scale, to assess SC maintain strong reliability, validity, and sensitivity across multiple populations—including college students, nurses, teachers, elders, and diverse range of ethnocultural groups (Barth et al., 1983; DeLiema et al., 2012; Kidd, 2007; Russell, 1996). The UCLA Loneliness Scale, for example, provides a unidimensional, global measure of loneliness, reliably predicting a range of outcomes related to interpersonal adequacy, health, and well-being (Russell et al., 1978). Correlational research demonstrates that higher loneliness scores correspond with lower levels of perceived social support, confirming construct validity in capturing the absence of connectedness. While more nuanced tools like the SCI offer detailed

profiles for targeted intervention, the widespread use of loneliness-focused scales, such as the UCLA Loneliness Scale, is justified for both research and clinical assessment: it is concise, psychometrically sound, and effectively indexes the core psychological state underlying social disconnectedness, thus serving as a practical and theoretically aligned proxy for measuring SC (Deol et al., 2022; Kelley et al., 2025; Russell et al., 1978; Russell, 1996).

Loneliness and Social Isolation

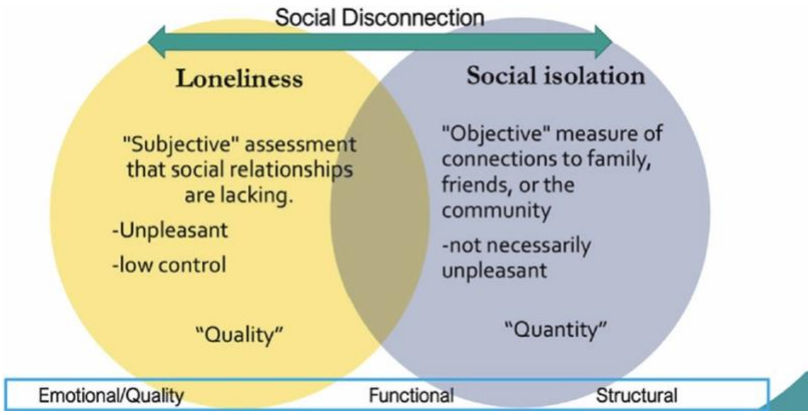
Loneliness and social isolation are considered features of social disconnection (see Figure 1). Loneliness, the "subjective" belief that one's social relationships are lacking, is an inherently negative experience (Kotwal et al., 2021; Perissinotto, 2024; Russell et al., 1978). An individual experiencing loneliness has a low sense of control over their social experience (Kotwal et al., 2021; Perissinotto, 2024). Social isolation, on the other hand, is the "objective" level of connection to family, friends, or community (Kotwal et al., 2021; Perissinotto, 2024). Unlike loneliness, social isolation is not an inherently negative experience (Kotwal et al., 2021; Perissinotto, 2024). Some individuals may seek out social isolation for various reasons or feel more comfortable maintaining social distance from others (Kotwal et al., 2021; Perissinotto, 2024). Individual control is also more complex, as some individuals may choose social isolation, thus experiencing high control, while others may be forced into isolation due to environmental factors, such as the Stay At Home Orders of the COVID-19 Pandemic. Conceptually, loneliness represents a reduced *quality* of social connections, while social isolation reflects the low *quantity* of social connections (Kotwal et al., 2021; Perissinotto, 2024).

There is also an abundance of research exploring social isolation and its relationship to SMU. Hikikomori, a term describing severe, prolonged social withdrawal, is referenced by many contemporary researchers. A key study differentiated between *problematic* hikikomori, when an

individual meets the criteria for hikikomori and experiences significant distress, and *non-problematic* hikikomori, when an individual meets the criteria for hikikomori but experiences no distress (Gavin et al., 2025). In sum, social isolation may be chosen and is not inherently a negative experience for individuals (e.g., sense of control, high or low loneliness). The present study does not seek to understand the relationship between SC and social isolation, as these are mutually exclusive, regardless of the type of isolation (problematic vs non-problematic). Instead, the focus of this study is centered on SC, in which loneliness represents the feelings and perceptions of SC, with low levels of loneliness representing high perceived SC, and high levels of loneliness representing low perceived SC.

Figure 1

The Spectrum of Social Disconnection: Distinctions Between Loneliness and Social Isolation



**Note: This figure was adapted from Kotwal et al., 2021, presented by Carla Perissinotto on April 29, 2024.*

ASMU, PSMU, and Social Connectedness

As evidence expands on the importance of social connection as a key aspect of mental health, researchers are increasingly examining the complex relationship between SMU and SC. Longitudinal studies show that while higher average SMU is associated with greater reported SC

at the between-person level, moment-to-moment (hourly) use—especially when interacting with peers—SMU can lead to decreased feelings of connectedness and increased social craving at the intrapersonal level (Armstrong-Carter et al., 2023). Susceptibility to peer influence emerges as a key moderator of these outcomes; for example, adolescents who are more influenced by peers tend to feel less connected and experience greater social craving after frequent SMU, suggesting that individual differences can significantly shape digital social experiences (Armstrong-Carter et al., 2023). These findings are focused primarily on the overall time spent using SM, rather than the type or depth of engagement on SM platforms.

The current findings focused specifically on PSMU and ASMU are mixed. Many studies have found positive associations between ASMU, SC, and overall well-being (Burke, 2025; Deters & Mehl, 2013; Hunt et al., 2021; Kraut et al., 1998; Verduyn et al., 2017), and between PSMU and loneliness (Hunt et al., 2021), leading to a consistent representation of ASMU as a tool for SC compared to PSMU. However, both recent and longitudinal data challenge the assumption that higher engagement on SM—such as posting or directly interacting with others—necessarily equates to higher levels of SC (Krause et al., 2023). A nine-year longitudinal study found that both PSMU and ASMU were associated with greater loneliness over time (Craine et al., 2025; Roberts et al., 2014). These findings contest previously held beliefs that active participation mitigates the isolating effects of passive online consumption, showing that even engaging with others online may not provide the same depth or quality of connection as face-to-face relationships (Roberts et al., 2014). Meta-analytic reviews and large cohort studies further complicate sweeping statements of SMU, revealing that SM's effects differ based on user motivations, quality of interactions, and individual vulnerabilities. For instance, those turning to SM due to existing loneliness or social anxiety are more likely to experience negative feedback

loops, as digital engagement may fall short in alleviating underlying needs for belonging and meaningful contact (Roberts et al., 2014). Conversely, individuals who use SM to supplement rather than replace real-world connections tend to report more stable levels of SC (Armstrong-Carter et al., 2023). Individual differences in neural reward systems also complicate assumptions of SMU. A notable study combining self-report and fMRI data found that neurotypical individuals, those with high neural reward sensitivity, are more likely to experience loneliness and social dissatisfaction from PSMU (Dziura et al., 2023). Neurodivergent participants, those with low neural reward sensitivity, showed positive associations between PSMU and social connectivity and satisfaction (Dziura et al., 2023). Dziura et al. (2023) conclude that for low reward-sensitive individuals, the ability to passively view social content online not only meets the social well-being needs of these individuals, but can also maintain needs over time.

The Life Course Theory and Other Theoretical Perspectives

Life Course Theory views human development as a lifelong process shaped by age-graded transitions, social roles, and historical context, emphasizing trajectories, transitions, and turning points from birth to death (Macmillan, 2005). It posits that individual lives unfold within socio-historical structures that create cumulative advantage or disadvantage over time, linking early-life conditions and exposures to later outcomes (Jones et al., 2019). The theory also highlights human agency and "linked lives," arguing that people actively construct their life paths within the constraints of their circumstances and interconnected social relationships (Yoshioka & Noguchi, 2009). This theory helps explain that there are several factors that influence the relationship between SMU and SC across different age groups, as well as why different groups rely on SM to feel connected to others, why SMU may negatively impact feelings of connectedness among one age group and not another, or why SMU is uniquely

positioned to provide some individuals with social benefits but not others. An individual's social needs are not solely based on temperament and personality but are largely tied to developmental stages as well as societal and cultural factors that influence these stages.

Life Course Theory highlights the unique developmental contexts and needs of, for example, emerging adults compared to middle adults. Emerging adults often experience losses of structured social and practical supports, such as the supports found in schools and family homes (Wood et al., 2018). The transitional period of early adult life is marked by developmental milestones, both physical, such as finalization of adolescence and brain development (Wood et al., 2018), and social changes, such as the beginning of university life away from home, or the first full-time professional job after high school (Eliason et al., 2015). In contrast, middle adulthood is uniquely characterized within the life course by a shift toward generativity and long-term contribution, as individuals increasingly focus on guiding future generations, mentoring others, and creating a lasting social impact rather than exploring identity as in earlier stages (Kuther & Burnell, 2019; Reinilä et al., 2023). Unlike earlier life stages centered on role acquisition, middle adulthood involves complex role integration across multiple domains**,** including career consolidation, caregiving for both children and aging parents, and preparation for later life transitions, reflecting its position as a pivotal "linking" stage in the life course (Lachman, 2015). This phase is distinct in that it represents a period of relative stability paired with adaptive psychosocial growth, where individuals refine identity, reassess life goals, and respond to age-graded challenges that shape trajectories into older adulthood (Heckhausen et al., 2010; Kuther & Burnell, 2019)

From a life course perspective, the mental health impact of SMU varies by developmental stage because age-graded roles and psychosocial needs shape how individuals

engage with online environments, with emerging adults—who are navigating identity formation and social belonging—showing distinct patterns of both benefit and risk depending on how they use these platforms (Keum et al., 2022). The theory also helps explain why there may be differences in mental health outcomes of ASMU and PSMU, as mental health outcomes are shaped by the interaction between developmental timing, social context, and behavioral patterns**,** such that the same type of SMU may have different psychological consequences depending on an individual's stage of life, available social roles, and cumulative experiences (Lewin et al., 2023; Wang et al., 2025).

Additional psychological theories help explain the divergent effects of SMU. Although not the primary foci of this study, they are worth taking into consideration. Social Comparison Theory (SCT), originally proposed by Festinger (1954), posits that individuals have an innate drive to evaluate their abilities, opinions, and worth by comparing themselves to others. When objective standards for evaluation are unavailable, people rely on social comparison as a self-assessment mechanism. Two major directions for social comparison exist, including *upward* comparison, where individuals compare themselves to others perceived as better off, and *downward* comparison, where individuals compare themselves to those seen as worse off. These comparisons influence emotional and cognitive outcomes. Upward comparisons can inspire self-improvement, but often lead to envy, lowered self-esteem, loneliness, and depressive symptoms (Appel et al., 2016; Verduyn et al., 2020). Downward social comparisons, on the other hand, can temporarily boost self-worth, but may foster disengagement or complacency. (R. H. Smith, 2000; Wills, 1981)**.**

SM platforms amplify these processes by providing constant, curated access to others' lives, often emphasizing idealized content. Research shows that PSMU increases opportunities

for upward comparison, triggering negative emotional outcomes (Appel et al., 2016; Verduyn et al., 2020), while ASMU can moderate these effects by fostering reciprocal interaction and social support, which may counteract the negative effects of social comparison (Frison & Eggermont, 2016; Yang, 2016). The focus of the comparison also moderates the effect of negative outcomes. For example, comparisons involving lifestyle or achievement are linked to reduced life satisfaction (Lup et al., 2015), and appearance-based comparisons are particularly linked to body dissatisfaction and self-objectification, particularly in upward comparisons on apps such as Instagram (Fardouly & Vartanian, 2016). Meta-analytic evidence finds that social comparison mediates the relationship between SMU and depressive symptoms (Jan et al., 2017; Yang, 2016). Thus, SCT provides a robust framework for understanding how the constant flow of social information on digital platforms can both connect and harm users, depending on the nature of comparisons, platform features, and user engagement styles.

Importantly, the SCT suggests that perceived similarity between the self and the comparison target influences the emotional impact; comparisons with peers or friends tend to elicit stronger emotional responses than with strangers or celebrities (Vogel et al., 2014). However, research testing this aspect of social comparison in regard to SMU has found that negative associations between loneliness and following real friends, and positive associations between depression and following strangers (Hunt et al., 2021). SCT suggests that users, especially passive ones, are prone to compare themselves unfavorably with others, which can reduce self-esteem and increase depressive symptoms (Verduyn et al., 2017).

The displacement hypothesis posits that time spent online displaces offline, meaningful social interactions, which could erode well-being (Orben, 2020). The underlying mechanism suggests that since time is finite, greater involvement in online environments reduces investment

in offline, in-person social, emotional, and community relationships that are typically more rewarding and psychologically protective. In an early longitudinal study of 169 participants from 73 households, Kraut et al. (1998) found that increased internet use was directly associated with declines in family communication, social circles, and well-being, specifically loneliness and depression. More recent studies extend this framework from the broader internet to SM contexts, finding that PSMU can heighten loneliness, social comparison, and depressive symptoms, consistent with displacement effects (Verduyn et al., 2017). In contrast, ASMU may counteract displacement by fostering reciprocal communication and maintaining or strengthening offline ties, particularly in cases of personalized communication between close friends (Burke & Kraut, 2016). Thus, within the displacement framework, it is not the quantity of time spent online, but the quality and interactivity of engagement that may determine whether SMU erodes or enhances well-being.

In contrast, the Rich-Get-Richer Hypothesis holds that individuals who are already socially competent may benefit more from SM, amplifying existing social advantages (Kraut et al., 2002) In the context of SMU, this hypothesis posits that people with higher baseline levels of connectedness, self-esteem, social competence, or extroversion, are better positioned to engage in active SM behaviors, which can in turn strengthen relationships and reinforce feelings of belonging (Burke & Kraut, 2016; Kraut et al., 2002; Valkenburg et al., 2021). Conversely, individuals with limited offline connections or greater social anxiety may engage more in PSMU, which can intensify feelings of exclusion or comparison and reinforce perceived connectedness . The Rich-Get-Richer hypothesis underscores how individual differences moderate the impact of SM: those who are already socially “rich” can leverage online tools to

enhance well-being, while those who are socially "poor" may not experience the same benefits and may even experience decline in mental health through passive engagement.

Finally, the Social Compensation Hypothesis contradicts the Rich-Get-Richer approach. This hypothesis proposes that individuals with limited offline social networks or lower social competence may use online platforms to compensate for real-world social deficits, allowing them to build or maintain connections that might otherwise be unavailable (McKenna & Bargh, 2000). In the context of SM, this theory suggests that people who are socially anxious, lonely, or introverted may derive greater social benefits from online interaction than their more socially connected peers (Manago et al., 2012). These compensatory effects are especially evident in ASMU (Nowland et al., 2018). In contrast, PSMU may not provide the same benefits, as it lacks the mutual engagement necessary to foster genuine social connection (Verduyn et al., 2017). However, recent studies indicate that the compensatory benefits of ASMU are not universal, depending on contextual and individual factors such as self-disclosure comfort, platform norms, and emotion regulation skills (Beyens et al., 2020). Overall, the social compensation framework highlights how active engagement online can serve as a coping and connection mechanism for those with weaker offline ties, though its efficacy varies across user characteristics and media contexts.

Notably, each of these theoretical frameworks and mechanisms emphasizes the potential for more positive outcomes of SMU, particularly among individuals engaging in ASMU. However, inconsistent results from studies exploring PSMU suggest that the downsides may not be as significant as previously believed.

Rationale for Review

Despite a growing volume of research, key gaps remain. For instance, few studies explicitly compare PSMU and ASMU in youth, adult, or elderly samples using standardized definitions and validated measures. Additionally, SC is often underexamined or explored indirectly through measures targeting general well-being or mental health. Reviews currently underway, such as Carroll et al.'s (n.d.) study, "Active and Passive Online Social Network Use in Middle-Aged and Older Adults: A Systematic Review of Associations with Psychological Well-Being," provide broad range of outcomes, which do not relate directly to SC. Although Godard et al. (2024) assessed the effects of PSMU and ASMU on loneliness, global social support, online social support, and general wellbeing among other variables, there is no inclusion of or explicit focus on SC. Hancock et al. (2022) explored the relationship between SMU and a variety of outcomes, including loneliness and social wellbeing, and tested the moderating effect of SMU type. However, this work lacks a comprehensive assessment of SC, or of the direct relationship between PSMU/ASMU and SC. Although some meta-analytic work has explicitly assessed social capital, a relevant form of SC, this work does not examine PSMU or ASMU (Liu et al., 2016). Furthermore, there is no consideration for age groups, which both use SM differently and have differing social needs. Several meta-analyses also include apps or sites such as WhatsApp, which, as discussed earlier, is not functionally a SM, and risks significantly obscuring any conclusions drawn about the relationship between SM and psychological or wellbeing outcomes (e.g., Marciano et al., 2024).

To the author's knowledge, there is no comprehensive review examining the associations between PSMU, ASMU, and SC across the lifespan which do not also include non-SMU apps such as WhatsApp or Yelp. Such a synthesis is crucial for contributing to evidence-based

recommendations to policymakers as countries around the world, such as Australia, Denmark, Indonesia, and Malaysia, have implemented bans, or plans for bans, of SMU for youth, although the fidelity and success of these bans vary (Wee & Chung, 2026). Caregivers, educators, and practitioners currently navigate the digital environment daily, and understanding potential associations between types of SMU and SC outcomes can influence parenting practices. Moreover, this review illuminates underlying mechanisms and identifies moderators, informing future research. The current study aims to fill this gap by reviewing and synthesizing available data on the associations between PSMU and ASMU and SC among youth.

Objectives

The primary objective of this meta-analytic review is to assess the current landscape of research on the differences in associations between PSMU and ASMU on SC. This systematic and meta-analytic review aims to answer the following questions:

1. Is there a significant association between PSMU and SC, and ASMU and SC?
2. Does age group moderate the strength of association between types of SMU and SC?
3. Does gender moderate the strength of association between types of SMU and SC?
4. Does the type of SC measured (e.g., SC, social support, belongingness) moderate the association between types of SMU and SC?

CHAPTER II

METHODS

Registration Information

The present study and study protocol were registered with the International Prospective Register of Systematic Reviews (PROSPERO) in accordance with PRISMA-P guidelines and can be found under the registration number CRD420261291662.

Criteria for Considering Studies Under this Review

The purpose of this study is to synthesize the current evidence on the association between PSMU and ASMU on SC. Studies were required to meet several eligibility criteria to be included in the present review.

Types of Studies

Eligible studies (see Table 1) were those that used a quantitative research design to examine the association between some measure of SMU and some measure of SC. Studies were required to report statistical data, such as means and standardized effects (i.e., Cohen's *d, r, ß)*, to be included. As such, purely qualitative studies were not included in this review. Experimental designs (e.g., randomized controlled trials; RCT) were included, although eligibility criteria resulted in none being present in the current review. Pre-experimental design studies were also included, as it was assumed there would be limited RCTs available. Observational studies were included in the present review. As with previous meta-analytic approaches (e.g., Stice, 2002), the effect sizes between the amount of ASMU/PSMU and SC can be examined for risk-outcome associations. As such, comparison groups were not required, and any studies that evaluated or compared groups engaging in low, medium, or high use of PSMU or ASMU were included. For many of the longitudinal studies, relevant data were only collected at baseline or in the cross-

sectional portion of the study. One longitudinal study observed differences in ASMU and PSMU and SC before and after COVID-19 pandemic. In this case, the later time point was used, as it more accurately reflects contemporary SMU. See Table 1 for more detailed information on study-level data.

Types of Participants

Eligible studies for this review included youth, emerging adult, middle adult, and older adult populations. The typical starting age for SMU is 8-12 years of age (Rideout et al., 2021), however, it was assumed that some studies analyzing independent SMU (e.g., no parental supervision) may incorporate younger individuals. To avoid excluding relevant studies, the "youth" age range was expanded from including youth aged 8 or older to also include youth aged 6 or older as the youngest possible participant age. Age groups were to be categorized into the following age demographics: ages 6-17, ages 18-29, ages 30-64, and ages 65 and older. The primary decision factor for these age groups was that much of the available research on SMU either groups individuals into these brackets or describes age groups using broad terms, such as "youth" or "older adult." It was expected that a majority of studies would align with the predetermined groups, and that some would not. As expected, many studies included some participants outside of these pre-determined age groups. For example, two studies conducted in university settings included a small number of participants aged 17, and one study included undergraduates aged 18 – 27. All of these studies had mean ages between 18 and 19 years. Such studies were considered part of the "emerging adult" group if the majority of participants were between the ages of 18 to 29. However, to account for potential differences based on researcher-developed age groupings, all studies received two labels of age category. For example, studies with M_{age}=19 were labeled "Emerging Adult" in one column ("age_groupxmean"), and studies

Table 1

Features of the Included Studies (k = 24)

Characteristic	*N* (%)
Study design	
Pre-Experimental Design	23 (100%)
Social Media Use Type	
Passive Use	18 (75.00%)
Active Use	22 (91.67%)
Country*	
United States (U.S.)	11 (43.85%)
China	5 (20.83%)
United Kingdom (U.K.)	3 (12.50%)
Australia	2 (8.33%)
Belgium	2 (8.33%)
Canada	1 (4.17%)
Germany	1 (4.17%)
Italy	1 (4.17%)
Netherlands	1 (4.17%)
Sample Setting*	
University	15 (62.50%)
Online	8 (33.33%)
Community Setting	3 (12.50%)
Social Media Platform	
Facebook	4 (16.66%)
Instagram	1 (4.14%)
QQ, WeChat, and Sina Wiebo	1 (4.14%)
Combination**	7 (29.17%)
In Discriminant	12 (50%)
Outcome Characteristics***	
Loneliness	18 (75.00%)
Social Support	7 (29.17%)
Belonging	4 (16.66%)
Social Connectedness	2 (8.33%)
Social Capital	1 (4.17%)

Notes. k refers to the number of studies providing data for rows with means and standard deviations. *Some studies had participants from multiple countries due to the type of data collection method (i.e., online surveys) or due to study design (e.g., Lin & Longobardi, 2025). **Several studies tested Facebook, Instagram, Snapchat, and Twitter together, along with one or

more additional sites (e.g., YouTube, Tumblr, Pinterest, or participant write-ins). ***Numbers do not add to 26 or100% as several studies collected data on multiple measures (e.g., loneliness in addition to belonging).

with *range* = 17–24 was labeled "Emerging Adult" in another column ("age_groupxrange"). Thus, studies were assigned two different age variables based on the reported means and age ranges ("youth," "emerging adult," "middle adult," "older adult," for mean-based categorization, with an additional option of "lifespan" for studies in the range-based categorization). There were no studies that disaggregated data between age groups (i.e., youth vs. emerging adult participants). Participants of all genders were included, and the present study provides a comprehensive report of participant demographic data (see Table 2).

Table 2

Participant Age and Gender Demographic Data

Participant Demographic Data	Mean (SD)	Range
Average Age (years)	26.02 (11.07)	14.3 – 69.84
Percent Male	33.54 (14.94)	12.85 – 57.01
Percent Female	64.31 (15.47)	31 – 85.4
Percent Gender Diverse	5.89 (12.25)	.34 – 30.9

Types of Conditions

Eligible conditions for the present study were focused on PSMU or ASMU. Studies included in this review differentiated between *passive* SMU (e.g., browsing, scrolling, viewing the profiles of others) and *active* SMU (e.g., posting, commenting, messaging). Studies that did not clearly differentiate between ASMU and PSMU, such as those that only evaluated general SMU, or studies that used methods to predict participant behavior rather than reporting actual behaviors, were not eligible for this review. Most studies reported composite scores across active or passive groups. However, some studies disaggregated SC scores based on types of active

behaviors or passive behaviors. For instance, one study reported SC outcomes for those who engaged in "broadcasting" or posting behaviors, in addition to reporting SC outcomes for direct messaging. In these instances, scores were averaged to establish a combined "active" score.

Types of Outcome Measures

The aim of the present study is to evaluate SC across the lifespan. As such, studies that focus on SC or closely related constructs were included. A comprehensive list of SC measures used in each study can be found in Appendix D. The present review included the Social Connectedness Scale – Revised (Lee et al., 2001), the UCLA Loneliness Scale (Russell, 1996), de Jong-Geirveld Loneliness Scale (1985), the Multidimensional Scale of Perceived Social Support (Zimet et al., 1988), Outpatient-Reported Outcomes Measurement Information System (PROMIS) Perceived Emotional Support Scale (Vogel et al., 2024), the Interpersonal Support and Evaluation List (Cohen & Hoberman, 2013), the Interpersonal Needs Questionnaire-15 (Van Orden et al., 2012), Relatedness and Interaction Belonging Scale, the Measure of Perceived Belonging (Gonsalkorale & Williams, 2007), the National Institute of Health Adult Toolbox Social Relationship Scales (Cyranowski et al., 2013), the Social Capital Scale (Erickson, 2011), and several researcher-developed questionnaires. Notably, there were several short-form scales used. For example, the 3-item, 7- item, 8-item, and 11-item versions of the UCLA Loneliness Scale were all used in included studies.

The inclusion of these measures is supported by previous research. Kelley et al. (1985) provide an expansive, although not complete, list of "well-established social connectedness instruments." Some of these include the Revised Social Connectedness Scale (Lee et al., 2001), the UCLA Loneliness Scale (Russell et al., 1978; Russell, 1996), the Multidimensional Scale of Perceived Social Support (Zimet et al., 1988), the Sense of Belonging Instrument (Hagerty &

Patusky, 1995). Of these, the most commonly used across the literature and within the included studies is the UCLA Loneliness Scale (Kelley et al., 2025). Notably, many of these measures focus on latent constructs, which are also aspects of SC, such as loneliness, social support, and belonging. As described by Kelley et al. (2025), these measures are consistently used across the scientific literature to explore the various components of SC. As such, the present study considered these and related measures as eligible for review. The present study also included studies with researcher-developed measures and studies that tested individual SC questions from a larger mental or social health questionnaire. Due to differences in directionality between various measures and study designs, all studies were assessed to identify whether high scores equated to positive or negative outcomes. All study effect sizes that presented high scores as negative (e.g., high scores indicated high loneliness) were multiplied by -1. This unified the directionality of all studies, such that high scores indicated positive outcomes (e.g., high SC or low loneliness), and low scores indicated negative outcomes (e.g., low SC or high loneliness).

Since the goal of this review was to assess overall SC, studies that only evaluated SC in the online environment were not eligible for review. Studies that utilized measures such as the Social Connectedness on Facebook Scale were excluded. Furthermore, any studies that replaced or edited measure questions to focus on a specific SM platform (e.g., "How connected do you feel to your friends *on Instagram*") were not eligible. Some studies elected to report subgroup outcomes on existing SC scales to report. For example, the 6-item de Jong-Gerveild Loneliness Scale (1985) contains 3-items directed at measuring emotional loneliness, and 3-items directed at social loneliness. In this case, the score for social loneliness was included, and the score for emotional loneliness was omitted, as social loneliness more closely aligns with SC as a construct. However, when studies reported multiple scores of the same SC measures, or when

scales were divided into several relevant SC types, a mean correlation score was calculated and reported.

Setting

All study settings were included in the present review. As expected, most studies utilized convenience sampling and were from university settings.

Language

Based on the linguistic capabilities of the research team, studies had to be reported in English.

Geography

Studies from all geographies were included, regardless of country, urbanicity, or rurality.

Date Available

Although many researchers consider the early 2000s the dawn of SM due to the popularization and accessibility of sites such as Facebook and MySpace, the first SM site was made accessible online in 1997 when Six Degrees, a social networking site that allowed users to create online profiles, became available to the public. As such, any articles published from 1997 onward were included in the search.

Search Methods for Identification of Studies

Electronic Searches

The initial search of key databases occurred between November 20th, 2025, and November 28th, 2025. Psychology & Behavioral Sciences Collection via ProQuest, ProQuest Social Science Premium Collection, PubMed, PsycINFO via APA PsycNet, and Communication & Mass Media Complete via EBSCO were searched. The preliminary search of these databases

was replicated on February 20th, 2026, to capture any additional articles that may have been released after the initial search.

Searching Other Resources

In addition to traditional peer-reviewed literature, this review included dissertations, conference papers, reports, and any relevant websites or organizations that report their own data (e.g., schools and states). Grey literature was searched using ProQuest Social Science Dissertations & Theses. Furthermore, all references from included studies were hand-searched. References from previous reviews (e.g., scoping, systematic, and meta-analytic reviews) were also examined for eligibility.

Search Strategy

The goal of this review was to evaluate the current research on the relationship between SC and PSMU and ASMU, including studies that only evaluated PSMU or ASMU. To that end, searches included terms geared at both PSMU and ASMU. The construct of SC warranted careful consideration, as many researchers collect participant data using measures such as the UCLA Loneliness Scale or individual items included in larger mental health assessments. To mitigate the loss of eligible studies, the search included various terms for mental health. To prevent the loss of eligible studies based on predetermined age groups, no age referencing or specifying terms were used in the search. Each term was required to be part of the title or abstract of the paper for several reasons. For example, due to the common use of SM as a recruitment strategy, it was essential to limit the inclusion of the term "social media" to the abstract of the paper. The term "social connectedness" and related outcome terms were also required to appear in abstracts or titles, as these are the outcome variables of the study. The sole filter used across all databases was the requirement that studies be available from January 1,

1997, and onward, as SM did not exist prior to 1997. This limited the potential for false positives from social science research testing "social networks" before the concept of online "social networks" became popularized in the research. Although each database had slight variations in formatting of searches (e.g., "AB()" vs "abstract()"), the same terms were used for every search. The following is the search used in the Social Science Premium Collection via ProQuest:

> abstract(connect* OR belong* OR isolat* OR lone* OR burden* OR hikikomori OR "mental health" OR "mental illness" OR "mental well*" OR "psychological distress" OR "psychological well-being" OR "social relation*" OR "social cohesion" OR "social support*" OR "social belong*" OR "social isolat*") AND abstract("social media" OR "social network*" OR Facebook OR Instagram OR Gram OR TikTok OR YouTube OR BeReal OR Discord OR Flickr OR LinkedIn OR Pinterest OR Reddit OR 4chan OR StumbleUpon OR Omegle OR Tumblr OR MySpace OR Threads OR Bluesky OR Vine OR DiVine OR YikYak OR Mastadon OR Lemon8 OR WeChat) AND abstract(Passive OR Lurk* OR Active OR Poster) AND pd(19970101-20251231)

Data Collection and Analysis

Selection of Studies

Study selection occurred in two phases. First, all studies found through electronic searches were compiled and stored on a systematic review management platform, Rayyan.ai. Five screeners and the study author reviewed each title and abstract to determine initial eligibility, so that each study was reviewed by the study author and one additional screener. Duplicate studies were removed. Due to the availability of resources during the title and abstract phase of screening (e.g., time, team member availability), studies were included if at least one team member identified them as relevant. Irrelevant studies, or studies that both screeners

identified as ineligible, were noted and separated from the eligible studies. Second, four screeners and the study author conducted full-text reviews of each study to determine final eligibility. All studies were reviewed by the study author and at least one additional screener. Studies were excluded based on outcome measures, condition type (e.g., no testing of PSMU or ASMU), study design (e.g., qualitative), not containing the necessary data (i.e., only containing means and standard deviations), and language. All disagreements on study eligibility were handled with discussion to reach consensus.

Extraction and Management

A systematic review management platform (Rayyan.ai) was used to organize all studies yielded from searches, store and screen full text articles, and identify duplicate studies. Google Sheets was used for data extraction, including identifying study data from multiple reports, and recording study effect sizes (e.g., Pearson's *r* or Regression test ß) for the specific outcome variables. A data-extraction table was created to collect and manage data, and the study author, in addition to two coders, extracted data from each included study such that all 24 included studies were double-coded. Study characteristic data were also collected, including, but not limited to, authors, publication year, sample size, gender percentages, study settings, study country, sampling methods, and study setting. All outcome variables, measures, and scales used, study timeframe, moderating effects and subgroup differences, main findings, limitations, funding sources, and all other relevant information were recorded. Statistical data collection included correlation data (e.g., zero-order correlations (*r*)) and standardized coefficients (ß) from regression analyses. For standardized coefficients of regressions, ß was assumed to represent partial correlations. If studies reported both partial and zero-order correlations, the partial correlations were prioritized to avoid biased results (Paul et al., 2025). Careful consideration was

made for these studies, and studies using partial correlations were considered for sensitivity analysis. All data were extracted, summarized, and charted for each included study (see Appendix D).

Study Risk of Bias Assessment

Three reviewers independently assess the included studies for risk of bias. Any disagreements between reviewers were resolved through discussion and consensus. Findings from the risk of bias assessment are presented in Appendix C, and a detailed narrative explanation of each evaluated element is provided. The evaluation of methodological risk of bias within the included studies followed established Cochrane procedures, drawing on the *Cochrane Handbook* (Sterne et al., 2019) and the recommendations of the Cochrane Consumers and Communication Review Group. In line with these standards, the review systematically examined and documented the relevant key bias domains in handling of incomplete data, outcome assessment, and selective reporting. Each domain was be rated as having a "low," "high," or "unclear" risk of bias based on the criteria described by Sterne et al. (2019), with supporting quotations and rationales provided in the risk of bias (see Appendix C). Due to the lack of RCT designs in the present review, random sequence generation and concealment of allocation domains are not relevant, thus they are not reported.

Study Characteristic Measures

There were several study characteristics that were recorded and operationalized in the present review (see Table 1). The definitions of these characteristics can be found in the Code Book (see Appendix A) and are provided in narrative form here.

Study Design. The present review includes studies of pre-experimental designs. Pre-experimental study design refers to studies that did not contain a control group.

Country. Most studies collected data from specific countries; however, some utilized online surveys for data collection, and others collected data from specific immigrant groups (e.g., Lin & Longobardi (2025) tested Chinese and Italian immigrant student populations). The country of the study location was reported when relevant; however, the countries of the participant groups were also reported, as this was often more relevant for studies using online data collection methods.

Sample Setting. The context of each study sample was recorded. A majority of studies utilized convenience sampling and recruited from university settings (k =14), followed by community settings (k = 2). Some samples were randomly recruited via online surveys (k = 4). Two studies utilized high school samples.

Social Media Platforms. Studies most often tested Facebook, Instagram, Twitter, and Snapchat all together, along with one additional site such as YouTube, Pinterest, or Tumblr. Although some studies tested Facebook (k = 4) or Instagram (k = 1) alone, the majority used various combinations of the most popular sites and some less popular sites (e.g., Tumblr).

Outcome Characteristics. Each measure used to collect scores on SC constructs was recorded (i.e., Multidimensional Social Support Scale). All scores were coded or reverse-coded so that high scores indicated more social connection and low scores indicated less social connection. Reverse coding was particularly relevant for the studies that utilized loneliness scales, as these coded high scores as more lonely and low scores as less lonely. Once scores were recorded and reverse coded as needed, the reviewers identified and recorded the primary construct each scale was designed to score. A study that implemented the UCLA Loneliness Scale, for example, was labeled "Loneliness" under "Constructs" so that moderation analyses could test differences in constructs moderated overall effects. Most studies included a measure of loneliness (k = 18), followed by social support (k = 5).

Participant Characteristics. As expected, most studies only reported "female" or "male" percentages of their samples. For the purposes of the present review, these groups were treated as cis females and cis males. Due to the low reporting on all other genders (e.g., nonbinary, Two Spirit) and identities (e.g., transfemale, transmale), non-cisgender participants were reported in the "Gender Diverse" category. See Table 2 for more detailed information about participant demographics.

Effect Size Measures

Effect sizes and their standard errors were calculated to quantify the relationship between the type of SMU and SC. The majority of studies reported Pearson's correlation coefficients as the measure of association; Five included studies reported standardized coefficients (ß) from direct path analyses. These were treated as Pearson's correlations (*r*) but noted as potentially partial correlations for sensitivity analyses. Observational studies examining the correlation between ASMU and SC, and/or PSMU and SC, represented the majority of the included studies (n=13). No included studies utilized control or comparison groups (e.g., no SM or neutral-use conditions), which eliminated the need to calculate Cohen's d between the active or passive group and the control group to accommodate inclusion of these contrasts in pooled analyses. Two approaches were used in cases where studies reported pre-post designs (n=2). For one, scores for outcome variables were reported in the cross-sectional data. As mentioned earlier, the second study reported SMU pre-COVID and post-COVID. Only the post-COVID SMU correlations were used, as they more accurately reflect contemporary SMU. Studies reporting adjusted group comparisons (e.g., regression-based estimates controlling for covariates), effect sizes were derived from regression coefficients or adjusted means, allowing incorporation of these controlled effects into the meta-analysis.

There were some studies that measured and reported effect sizes for multiple types of connectedness scales (e.g., Social Connectedness Scale and UCLA Loneliness Scale). All data were reported, however, since the primary goal of the present review is to evaluate SC, scores from SC scales were selected for analyses over scores from proximal measures, such as the Multidimensional Scale of Perceived Social Support or the UCLA Loneliness Scale. In cases where studies separated items from single scales into two subsections, a single effect size from the study was computed to maintain independence of observations, using an arithmetic mean. Some studies reported subsections that were more closely aligned with SC. For example, if a study reported the 3 items for social loneliness and the 3 items for emotional loneliness from the 6-item UCLA Loneliness Scale, the 3-item social loneliness effect sizes were recorded, reported, and used for analyses. Due to the variation in types of SC measurements used across the literature (e.g., Multidimensional Scale of Perceived Social Support vs. UCLA Loneliness Scale), each measure type was recorded, along with the matching effect size data, so that analyses could be run to evaluate differences based on the measures used. It is worth noting that one study (Sohn & Washington, 2025) included two separate populations within the same study and reported separate data for each population (Italian and Chinese university students). In this case, effect sizes for both populations were recorded and included in analyses, as there was no risk of violating independence of observations. All effect sizes, reported below in the Fisher's z-transformed metric, were accompanied by 95% confidence intervals and transformed into Fisher's z to facilitate pooled analyses, as proposed in Borenstein et al. (2021):

$$z_r = \frac{1}{2}\mathrm{In}\left(\frac{1+r}{1-r}\right)$$

Multiple Study Reports

There were no included studies that reported the same study information in multiple reports; rather, there were duplicate studies that were published separately, for example, dissertations that were later published in peer-reviewed journals. The peer-reviewed journal articles were selected over their grey literature counterparts. Thus, the present review only includes a single effect size to represent the eligible studies.

Missing Data

Studies included in the present review provided the necessary data for analysis (i.e., correlation data). Additionally, no studies failed to report the necessary information for evaluating risk of bias. Assessments followed the guidance of the chosen risk of bias tool to determine the appropriate level of bias for each relevant domain. For missing outcome or summary statistics, data imputation techniques were applied when feasible, and all assumptions made during imputation were explicitly documented. The impact of any imputed data on the overall pooled effect estimates was examined using sensitivity analyses to assess the robustness of the results.

Data Synthesis

To test RQ1: "Is there a significant relationship between PSMU and SC, and ASMU and SC?" the present review utilized a random-effects meta-analysis with inverse variance weights to estimate the overall mean effect size. The primary analysis included all studies for an overarching assessment of SC. To explore the effects of studies measuring SC alone, a separate analysis was run testing only the studies that reported SC. Due to the high rate of studies measuring SC exclusively through loneliness measures (e.g., the UCLA Loneliness Scale), a third analysis was conducted to evaluate whether there were significantly different outcomes

when separating the studies evaluating SC via loneliness. A fourth analysis, excluding measures of loneliness but including all other measures of SC, was conducted to assess whether effects were influenced by potential differences in constructs. To answer moderation research questions (RQ2, RQ3, and RQ4) a mixed effects meta-analysis with inverse variance weights and reported 95% CI with mean effect sizes was used, with age, gender, and constructs serving as moderating variables. All meta-analyses reported 95% CI with mean effect sizes and were displayed with forest plots. All analyses were performed using the 'metafor' package (Viechtbauer, 2010) in R (version 4.8.0) (R Core Team, 2026).

Assessment of Heterogeneity

The present study used restricted maximum likelihood (REML) estimation (Viechtbauer, 2010) and assessed heterogeneity utilizing both visual inspection of forest plots and examination of the Q, τ^2, and I^2 statistics. Prediction intervals of 95% were also used to assess the dispersion of effects and variance across studies. Consideration was given to the Q-test p-value, in accordance with Sterne et al. (2019), and the τ^2 statistic was used to evaluate the between-study variance. Subgroup analyses were conducted to understand heterogeneity in pooled effect estimates. The following subgroups were assessed: Studies that only evaluated loneliness, studies that evaluated SC outcomes other than loneliness, and studies that evaluated only SC. Additional analyses tested the potential moderating effects of age groups, gender, and SC construct (i.e., loneliness, social support, SC). Heterogeneity related to methodological or statistical outcomes is reported. Any decisions regarding study exclusion due to this type of heterogeneity was thoroughly explained and reported within the review.

Assessment of Reporting Biases

Publication bias was addressed by visually inspecting funnel plots to explore small-study effects. The symmetry of the funnel plot was formally assessed using the recommendations of Sterne et al. (2019), acknowledging that asymmetry can arise from multiple factors beyond publication bias. The trim-and-fill method was utilized (Duval & Tweedie, 2000), and Egger's regression test (Egger et al., 1997) was used to test for mean difference effect sizes. Additionally, a cumulative meta-analysis was conducted to examine whether the overall mean effect size changed when studies with smaller sample sizes were sequentially added.

Sensitivity Analysis

Sensitivity analyses were conducted and reported in both narrative and visual form via figures. Analyses were conducted to evaluate the level of risk of bias as well as the different ICC estimates used. In addition to testing moderation differences based on age-group, this review conducted meta-analyses excluding specific subgroups, such as studies that only evaluated loneliness and studies that used measures other than those explicitly testing SC, to evaluate the robustness of the overall effect.

CHAPTER III

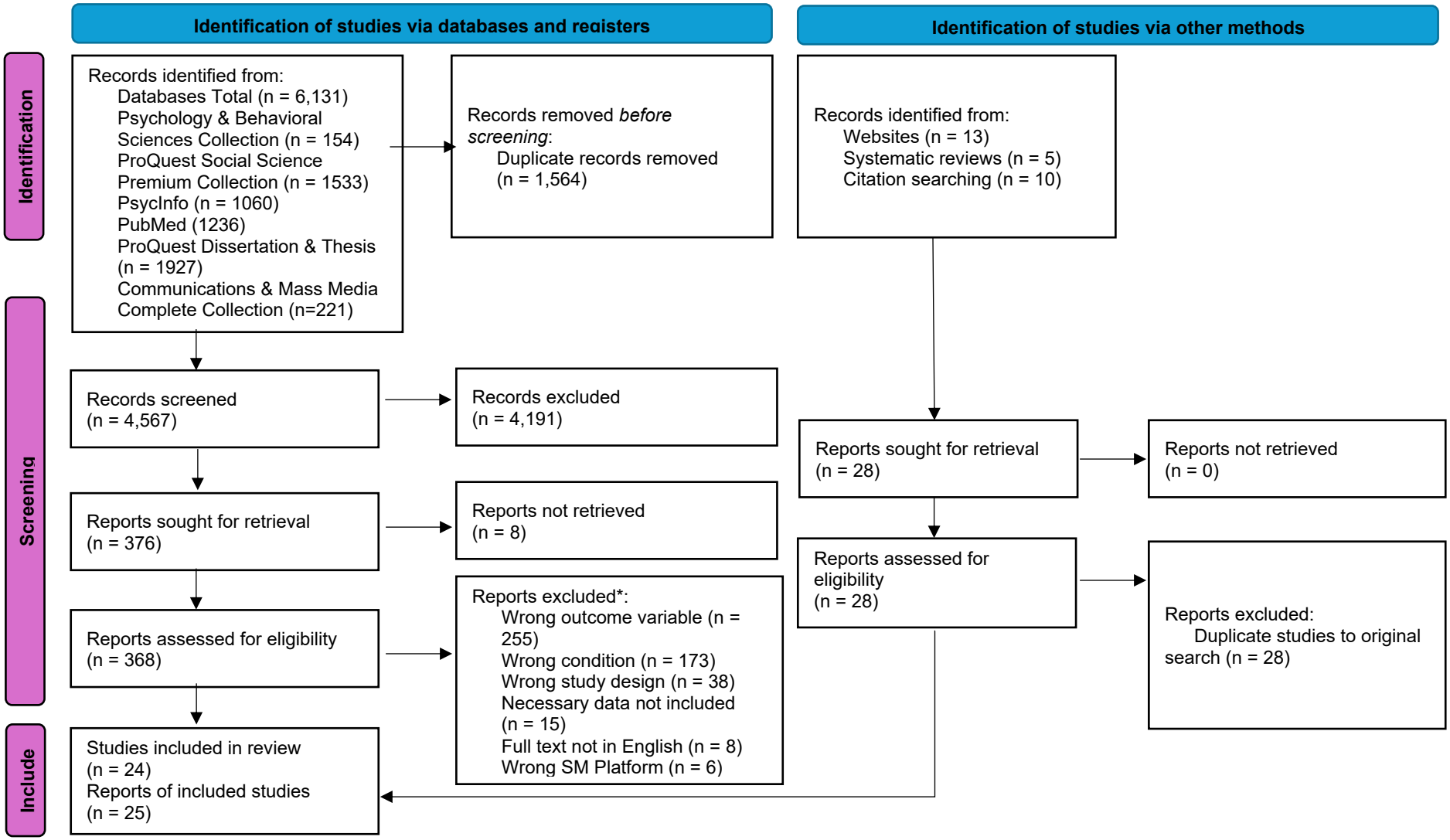
RESULTS

Search Results

A total of 6,131 studies were identified in the literature search. Of these, 1,564 were identified as duplicates and excluded. Studies were excluded for the wrong outcome (n = 255), the wrong condition (n = 173) or study design (n = 38), for not reporting the necessary data (n = 15), for not having full-text available in English (n = 8), and for testing the wrong SM platforms (n = 6). For more detailed information, see the PRIMSA Diagram in Figure 2. A final sample of 24 studies were included, which provided 25 independent sample effect sizes, and 32 total effect sizes (i.e., including studies that measured multiple SC constructs with the same participants). Of the included studies, 19 were published journal articles, and 5 were dissertations. A majority took place in the U.S. (k =11), followed by China (k = 5), the U.K. (k = 3), Australia (k = 2), Belgium (k = 2), Canada (k = 1), Germany (k = 1), Italy (k = 1) and the Netherlands (k = 1). One study recruited participants from Australia, the U.S., and the U.K (Tobin et al., 2015), and Lin and Longobardi (2025) collected data from both China and Italy.

Studies were primarily pre-experimental in design. Participants were predominantly female (M = 64.31, SD = 15.47), and of the emerging adult age group (M = 26.02, SD = 11.07). A majority utilized convenience sampling (k = 22) and recruited participants in university settings (k = 14). Studies were required to provide some definition of SM in order to be included; however, most studies did not report which SM apps were tested (k = 12). For single site studies, Facebook was the most often used SM for studies (k = 4), followed by Instagram (k = 1). Studies that tested Facebook, Instagram, Twitter, Snapchat (k = 4) also included a combination of one or more additional SM sites, such as YouTube, Tumblr, or Pinterest. One study tested QQ, WeChat, and Sina Weibo, which was appropriate considering

Figure 2: PRISMA Flow Chart



**Some studies were excluded for multiple reasons; therefore, the total number of studies does not add up to k = 368.*

the study setting was China. Although there are several studies that evaluated SC directly, a majority of included studies measured loneliness (k = 18). Social support was the second most utilized construct (k = 8), followed by belongingness (k = 5). Only two studies measured SC directly (i.e., utilizing the Social Connectedness Scale), and one measured Social Capital. To assess the risk of bias among studies, there were several data collected, including (a) handling of incomplete data, (b) outcome assessment, and (c) selective reporting. It is worth noting that three .of the 24 included studies did not report a mean age (O'Brien et al., 2021; Sohn & Washington, 2025; Zhao et al., 2023), and of the 21 studies that reported participant mean age, an additional four failed to report the standard deviations of mean age (Keum et al., 2022; Matook et al., 2015; Rothschild & Weissbrod, 2015; Vogel et al., 2024). Eight studies did not report the age ranges of the included participants (Aalbers et al., 2019; Matook et al., 2015; McNamara & Heimberg, 2023; Rothschild & Weissbrod, 2015; Taylor et al., 2024; Tobin et al. 2015; Vogel et al., 2024; Wang et al., 2018). Appendix D provides a comprehensive table of the included studies, along with the reported mean ages, standard deviations, and age ranges.

Results for Meta-Analyses

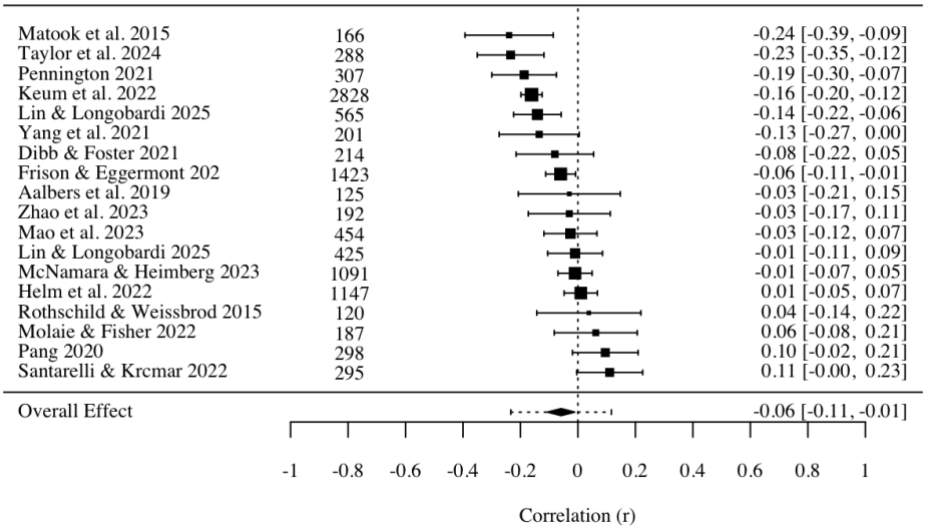
Passive Social Media Use

A random-effects meta-analysis was conducted across k = 17 studies that reported n = 18 effect sizes for PSMU. Lin and Longobardi (2025) recruited 565 Chinese university students from three universities in China, and 425 Italian university students from three universities in Northern Italy. Data from the Chinese and Italian samples were analyzed and reported separately, providing the present review with two independent effect sizes. All scores for SC measures were coded or reverse-coded so that higher scores indicated greater connectedness and lower scores indicated less connectedness. In the first model, the overall effect size was

significant, with an estimated mean effect of $\bar{z}$ = -0.06 (SE = 0.02), 95% CI [−0.11, -0.01], z = -2.41, p = .02, (see Figure 3). Thus, on average, higher levels of passive use were associated with lower levels of connectedness. There was substantial heterogeneity $Q(17) = 79.94$, $p < .001$. The I^2 statistic indicates that 79.52% of the variance in the observed effect sizes reflects variance in true effects rather than sampling error. The estimated between-study variance ($\tau^2 = 0.01$, SE = 0.00) and corresponding standard deviation of true effects ($\tau = 0.09$) suggested dispersion in effect sizes. The 95% prediction interval, defined as the interval within which the effect size of a new study would fall if this study were selected at random from the same population of studies, was wide [-0.23, 0.12]. Visual inspection of the funnel plot showed no clear indications of asymmetry. A trim-and-fill Analysis (see Figure 4) as well as an Egger's regression test was

Figure 3

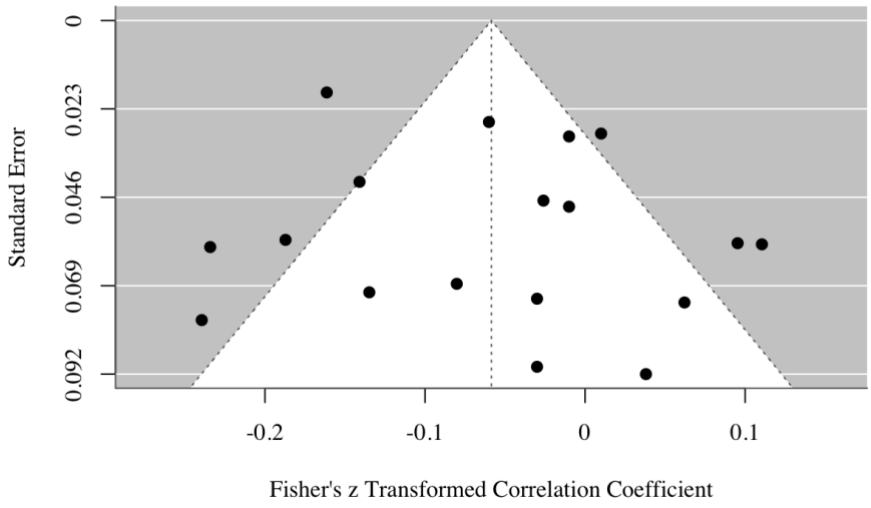
Forest Plot of Passive Social Media Use and all Social Connectedness Measures Meta-Analysis



conducted using a mixed-effects meta-analysis model to assess funnel plot asymmetry. The test was not significant, b = -0.07 (SE = 0.07), 95% CI [-0.21, 0.06], z = -1.14, p = .26, but revealed

Figure 4

Trim-and-Fill Funnel Plot of the Passive Social Media and Social Connectedness Meta-Analysis



substantial heterogeneity among effect sizes, Q(16) = 74.28, $p < .001$, with $I^2 = 79.99\%$, indicating that the majority of observed variability reflected true differences between studies rather than sampling error. The test for asymmetry was not significant ($z = 0.30$, $p = .77$), indicating no strong evidence of publication bias. Residual heterogeneity remained substantial ($\tau^2 = 0.09$, $I^2 = 79.99\%$), and the standard error predictor did not account for a proportion of variance ($R^2 = 0.00$), suggesting that small-study effects do not explain the observed variability.

A majority of studies reported negative mean effect sizes, and only five reported positive effects: Helm et al. (2022; 0.01 [-0.05, 0.07]) which measured loneliness, Rothschild and Weissbrod (2015; 0.04 [-0.14, 0.22]) which measured social connectedness, Molaie and Fisher (2022; 0.06 [-0.08, 0.21]), which measured belonging, Pang (2020; 0.10 [-0.02, 0.21]) which measured social support, and Santarelli and Krcmar (2022; 0.11 [-0.00, 0.23]) which measured

social connectedness. It is remarkable that the two studies explicitly measuring social connectedness included in this review (Rothschild & Weissbrod, 2015, and Santarelli & Krcmar, 2022), contributed two of the five effect sizes surpassing zero in this particular meta-analysis. These studies are explored in greater depth below, however, their contribution to the cumulative meta-analysis may suggest that these social connectedness constructs, while theoretically comparable to their subconstructs (e.g., loneliness and belonging), may capture slightly different psychological experiences. However, no conclusions should be drawn from the contributions of two studies alone. Although the overall mean effect size is small, it is significant, and 13 of the 18 included effect sizes showed negative effect sizes.

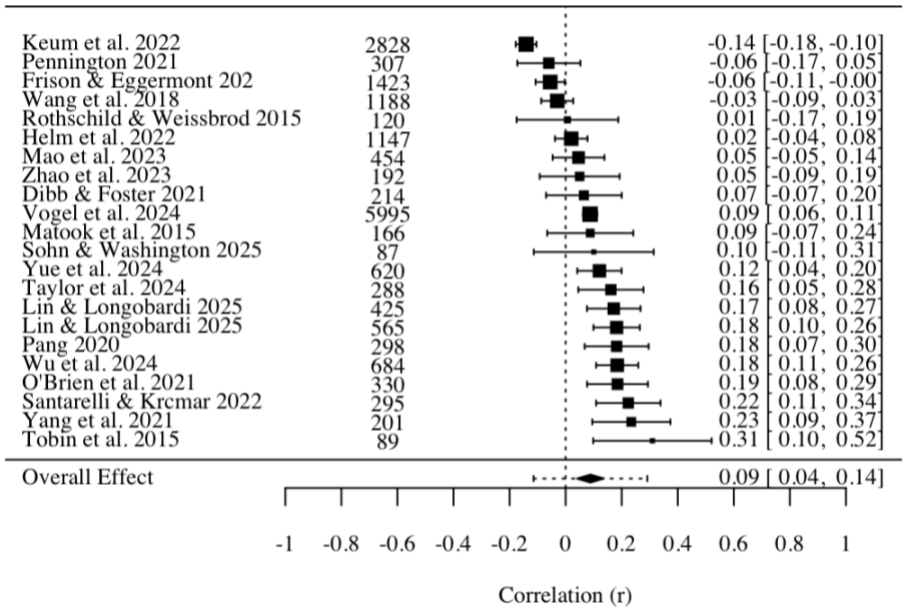
Active Social Media Use

A random-effects meta-analysis using restricted maximum likelihood (REML) estimation was conducted across 21 studies with 22 effect sizes (Figure 5). As with the PSMU analysis, Lin and Longobardi (2025) contributed two effect sizes from two independent samples. The estimated mean effect was significant ($\bar{z}$ = 0.09 [SE = 0.03], 95% CI [0.04, 0.14], $z = 3.60$, $p < .001$) and positive, suggesting that, on average, higher levels of active use were associated with higher levels of SC. There was substantial heterogeneity among studies, $Q(21) = 206.23$, $p < .001$, with $I^2 = 87.84\%$, $\tau^2 = 0.01$ (SE = 0.004), and $\tau = 0.1$, indicating that most variability reflects true between-study differences rather than sampling error. The prediction interval was wide, 95% PI [−0.11, 0.29], suggesting that the true effect may vary across contexts and could range from small negative to moderate positive effects. Only four of the 22 included effect sizes showed negative effects (Frison & Eggermont, 2020; Keum et al., 2022; Pennington, 2021; Wang et al., 2018). Each of these four studies measured loneliness. While this alone may not indicate the need to treat loneliness as a separate construct from social connectedness, the

included analyses below that remove loneliness from the larger SC model indicate there are unique contributing factors to this construct. Furthermore, while the overall mean effect of this model is small, the large sample size of Keum et al. (2022; *n* = 2828), and Frison and Eggermont (2020; *n* = 1423), and Wang et al. (2018; *n* = 1188) likely drive down the overall effect size.

Figure 5

Forest plot of Active Social Media Use and Social Connectedness Meta-Analysis

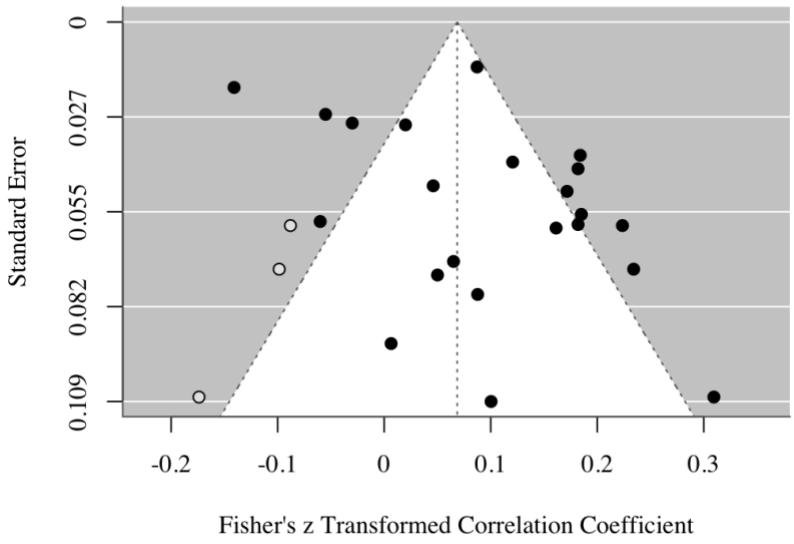


A funnel plot was created and visually inspected and did not reveal obvious asymmetry. A trim-and-fill analysis (see Figure 6) and an Egger's regression test were conducted using a mixed-effects meta-analysis model to assess funnel plot asymmetry across 22 effect sizes. The intercept was not statistically significant, $\bar{z}$ = -0.01 (SE = 0.05), 95% CI [−0.12, 0.09], z = -0.30, p = .80, and the test for asymmetry was significant (z = 2.12, p < .05), suggesting that there is evidence of publication bias. In other words, results suggest that smaller studies display different effect sizes compared to larger studies, and since small studies with negative, neutral, or non-significant results are less likely to be published, there is a gap in the plot. Residual

heterogeneity remained substantial, $\tau^2 = 0.01$ (SE = 0.00), $I^2 = 84.22\%$, and the standard error predictor accounted for a modest proportion of variance ($R^2 = .20$), suggesting that small-study effects may contribute to variability.

Figure 6

Trim-and-Fill Funnel Plot of Active Social Media Use and Social Connectedness Constructs



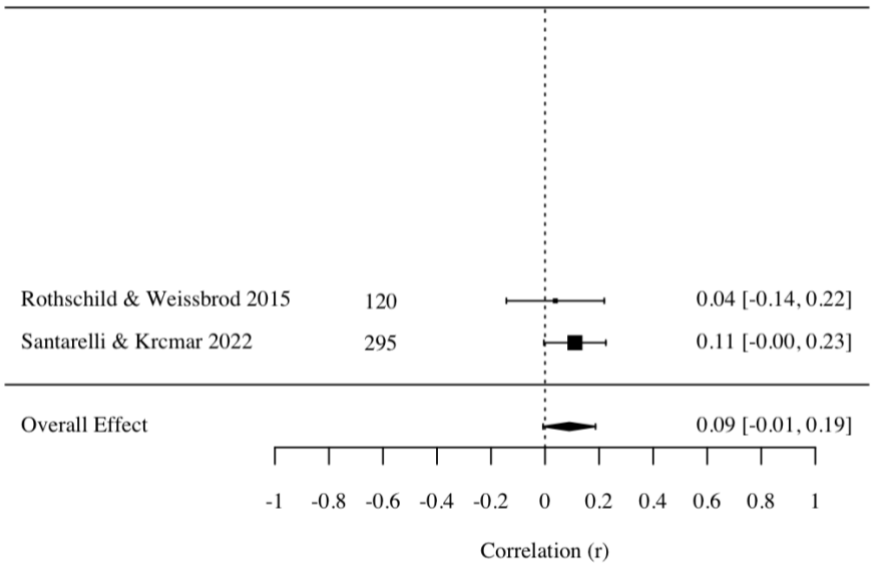
Connectedness Only

When restricting analyses to studies ($k = 2$) that directly measured SC (e.g., using the Social Connectedness Scale), the pooled effect remained small and non-significant for PSMU ($\bar{z} = 0.09$ [SE = .05], 95% CI [−.01, .19], $z = 1.81$, $p = .06$; see Figure 7). It is notable that the small effect size was positive, as previous literature would suggest this relationship should be negative, and that high PSMU is related to low connectedness. However, the null positive mean effect size may simply reflect low statistical power, thus caution is warranted when drawing conclusions from this particular analysis. There was no detectable residual heterogeneity ($Q[1] = 0.44$, $p = .51$ with $I^2 = 0\%$). Due to the small number of studies, small-study effects were not

meaningful (τ^2 = 0.0 [SE = 0.01], τ = 0). The 95% prediction interval was moderately wide [-0.01, 0.19], suggesting the true effect may vary across contexts, and future studies may yield effect sizes of small negative to positive values. Due to the small number of studies included (*k* = 2), a funnel plot inspection, trim-and-fill analysis, and Egger's regression test were not conducted.

Figure 7

Forest plot of Passive Social Media Use and Only Social Connectedness

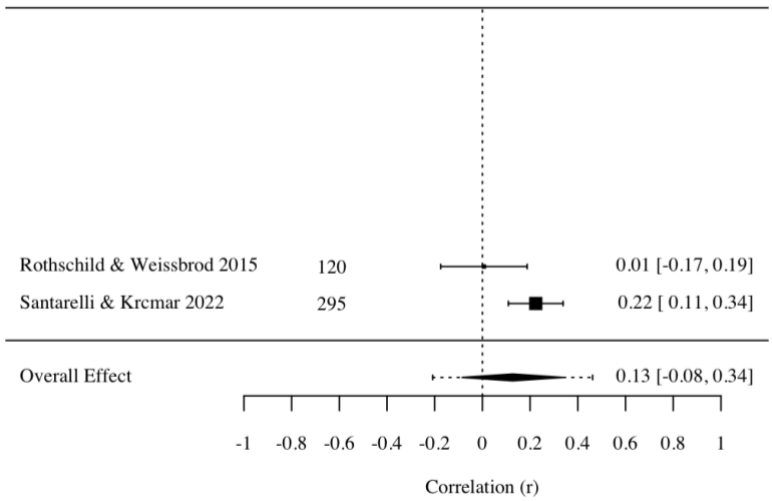


When ASMU studies were restricted to studies measuring SC directly, the pooled effect size was positive but non-significant, $\bar{z}$ = 0.13 (SE = 0.11), 95% CI [−.08, .34], z = 1.18, p = .24. There was also substantial heterogeneity among studies (Q[1] = 3.94, p < .05, I^2 = 74.61%, τ^2 = 0.02 [SE = 0.03], and τ = 0.1), although this is not particularly meaningful considering the low number of included studies (k = 2). The 95% prediction interval [-0.21, 0.46] suggested that the true effects varied, and may span between negative and positive values. Figure 8 illustrates the forest plot for this analysis. The small number of studies included in both of these analyses (k = 2) likely contributed to the results for subgroup analyses. Funnel plot inspection, trim-and-fill

analysis, and the Egger's regression test were not conducted due to the small number of studies (k = 2).

Figure 8

Forest plot of Active Social Media Use and Only Social Connectedness



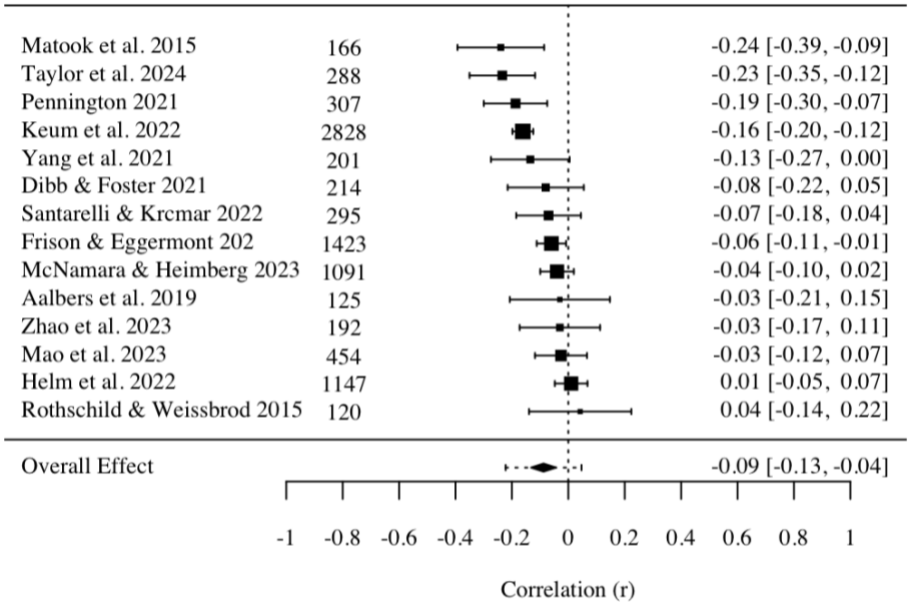
Loneliness Only

A separate analysis of studies examining loneliness was conducted for the 14 studies evaluating loneliness and PSMU (see Figure 9). The analysis yielded a significant estimated mean effect for PSMU studies, $\bar{z}$ = -0.09, (SE = 0.02), 95% CI [-.13, -.04], z = -3.88, p < .001. Since loneliness scores were reverse coded such that higher scores indicated more connectedness and less loneliness, and lower scores indicated less connectedness and more loneliness, the negative mean effect of the present model suggests that higher levels of PSMU are associated with lower levels of SC. In other words, more passive use was associated with more loneliness, which aligns with previous research. Only two studies in this model yielded negative effect sizes: Helm et al. (2022) and Rothschild and Weissbrod (2015). Although the overall mean effect is small, this may, in part, be due to the large sample size (n = 1147) of Helm et al. (2022),

which could have driven up the mean. Heterogeneity across studies was significant, $Q(13) = 47.74$, $p < .001$, with $I^2 = 70.24\%$, indicating that the majority of observed variability reflects true differences between studies rather than sampling error. The estimated between-study variance ($\tau^2 = 0.00$, SE = 0.00) and corresponding $\tau = 0.06$ was low. The 95% prediction interval was moderately wide [-0.22, 0.05], indicating that true effects may range from negative to small positive values.

Figure 9

Forest Plot of Passive Social Media Use and Loneliness

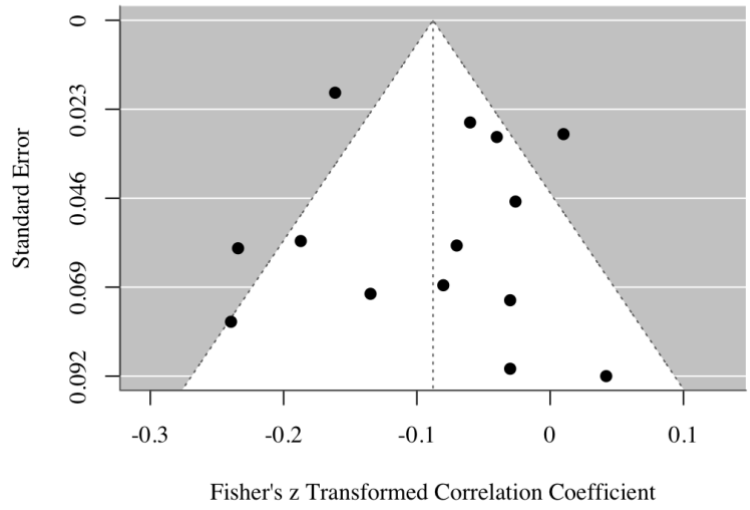


Inspection of the funnel plot did not suggest asymmetry. Trim-and-fill analysis (Figure 10) along with the Egger's regression test showed the intercept was statistically non-significant, $\bar{z} = -0.08$ (SE = 0.06), 95% CI [−0.19, 0.03], $z = -1.35$, $p = .18$, and the test for asymmetry was also non-significant, $z = -0.22$, $p = .83$, indicating no evidence of publication bias. Residual heterogeneity remained high, $\tau^2 = 0.01$ (SE = 0.00), $I^2 = 71.75\%$, however, notably, the Egger's regression

model did not account for any of this variability (R^2 = .00), indicating that differences in study precision or sample size do not explain the observed dispersion in effects.

Figure 10

Trim-and-Fill Funnel Plot of Passive Social Media Use and Loneliness

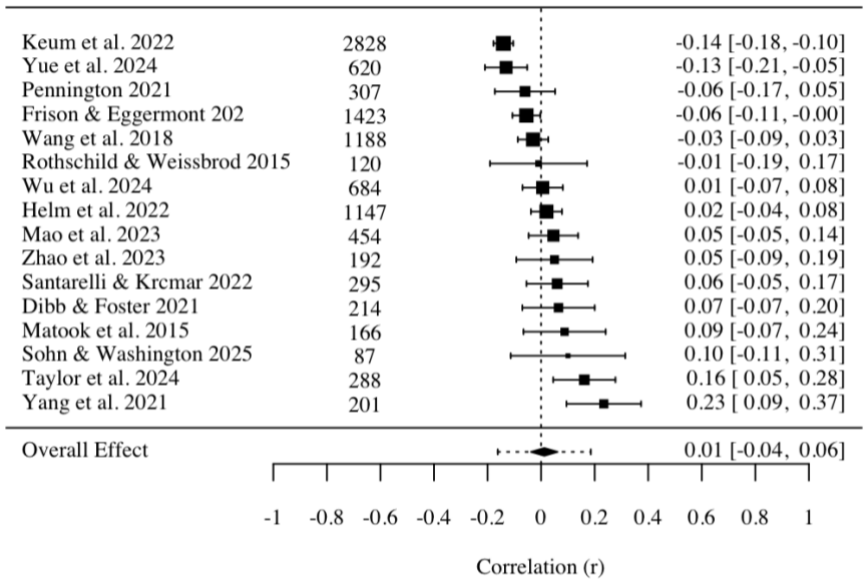


Another analysis between ASMU and loneliness was conducted across 16 studies (see Figure 11). The overall effect size was small and not statistically significant ($\bar{z}$ = 0.01 [SE = 0.03], 95% CI [−0.04, 0.06] z = .47, p = .64). Six of the 16 studies had negative effect sizes. Of these, three had large sample sizes, including Wang et al. (2018; *n* = 1188), Frison and Eggermont (2022; *n* = 1423), and Keum et al. (2022; *n* = 2828) which likely contributed to the small effect size. This is particularly important since 9 of the 10 studies with positive effect sizes had sample sizes of *n* = 684 or less, and 7 had sample sizes of less than *n* = 300.

There was substantial heterogeneity among effect sizes, $Q(15) = 80.97$, $p < .001$, with $I^2 = 80.85\%$, indicating that the majority of variability reflects true differences between studies rather than sampling error. The estimated between-study variance was $\tau^2 = 0.01$ (SE = 0.00),

Figure 11

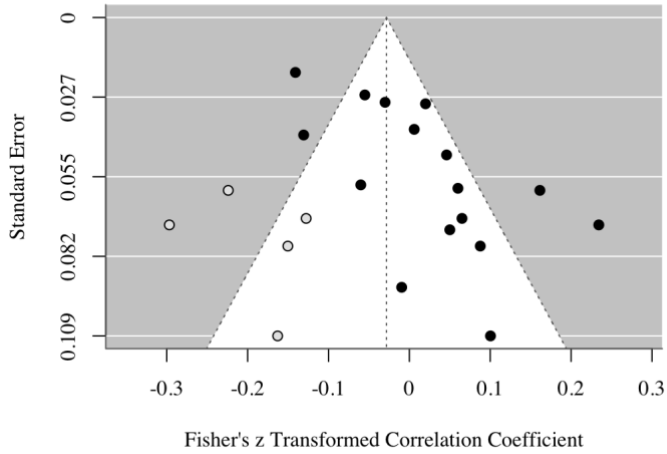
Forest Plot of Active Social Media Use and Loneliness



95% CI [-0.04, 0.06], with a corresponding τ of 0.09, suggesting a relatively small range in the accuracy of effect size. The 95% prediction interval was wide [−0.16, 0.19], indicating that true effects may range from small negative to small positive values. Visual inspection of a funnel plot demonstrated asymmetry. A trim-and-fill analysis (see Figure 12) and Egger's regression test were conducted using a mixed-effects meta-analysis model to assess funnel plot asymmetry across the 14 studies. The intercept was statistically significant, $\bar{z}$ = -0.13 (SE = 0.05), 95% CI [-0.22, -0.04], z = -2.74, p < .01, and the test for asymmetry was statistically significant, z = 3.11, p < .001. Residual heterogeneity was moderate, τ^2 = 0.00 (SE = 0.00), I^2 = 65.38%, and the standard error predictor accounted for a large proportion of variance (R^2 = .54). The results suggest that there were small-study effects which contributed to the observed variability. Additionally, the results indicate that there is evidence of publication bias across the sample of studies.

Figure 12

Trim-and-Fill Funnel Plot of Active Social Media and Loneliness

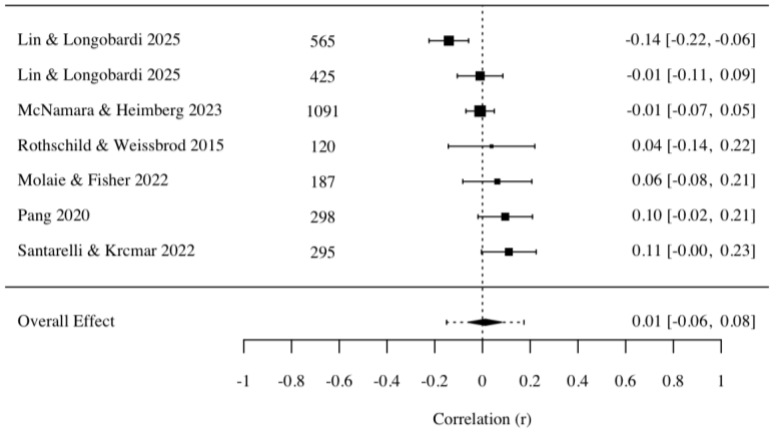


Social Connectedness Excluding Loneliness

When loneliness was excluded and analyses focused on other indicators of social connection (e.g., social support, belonging, social capital; see Figure 13 for the Forest Plot), the

Figure 13

Forest Plot of Passive Social Media Use and Social Connectedness Measures, Excluding Loneliness

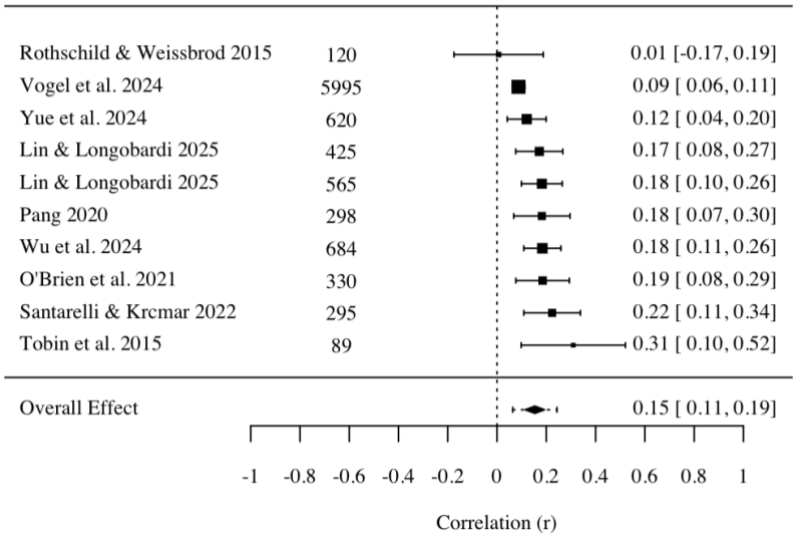


overall association remained non-significant for PSMU studies (k = 7; $\bar{z}$ = 0.01, [SE = 0.04], 95% CI [−0.06, 0.08], z = 0.33, p = .74). Heterogeneity was moderate (Q[6] = 18.32, p < .05, I^2 = 68.34%), indicating that some of the observed variability reflects true differences between studies rather than sampling error. The estimated between-study variance (τ^2 = 0.01, SE = 0.01) and corresponding τ = 0.07 were low. The 95% prediction interval was moderately wide [-0.15, 0.17]. Funnel plot inspection, trim-and-fill analysis, and Egger's regression test were not conducted due to the low number of included studies.

However, the ASMU model (Figure 14), which included 10 effect sizes from k = 9 studies, demonstrated a positive association ($\bar{z}$ = .15 [SE = 0.02], 95% CI [.11, .19], z = 7.63, p < .001). This suggests that among the included constructs, higher levels of ASMU were associated with higher levels of SC, on average. None of the 10 included effect sizes were negative, and only one study had confidence intervals that surpassed zero. First, this suggests there is stronger evidence that higher levels of ASMU are associated with higher levels of SC.

Figure 14

Forest Plot of Active Social Media Use and Non-Loneliness Constructs

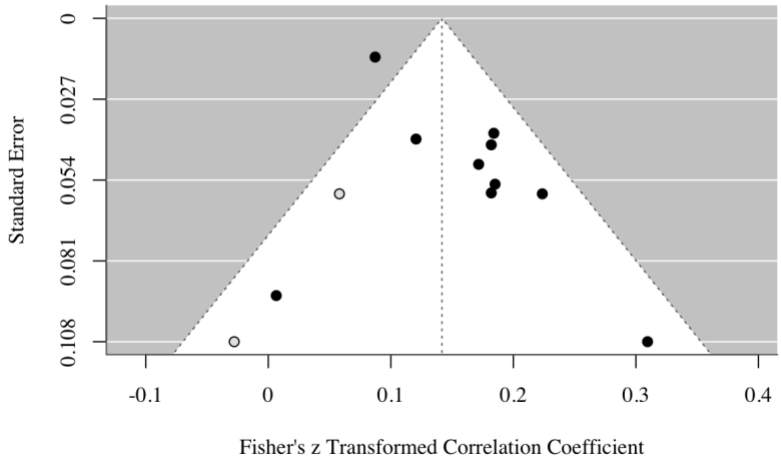


Second, this suggests that there may be unique qualities to the construct of loneliness, either conceptually or within the included measurement tools, that distinguish it from the other SC constructs included in this study.

Heterogeneity in this model was notably lower compared to previous analyses (Q[9] = 22.71, p < .05, I^2 = 50.31%), indicating some variability across studies when conceptually similar constructs were analyzed together. Between-study variance (τ^2 = 0.00, SE = 0.02, 95% CI [0.00, 0.01]) was small in magnitude, indicating limited between-study variability. The 95% prediction interval was narrow [0.06, 0.24], suggesting that the effects of a randomly selected study are likely to remain positive and fall within a relatively limited range. Inspection of the funnel plot suggested asymmetry, which was supported by trim-and-fill analysis (see Figure 15).

Figure 15

Trim-and-Fill Funnel Plot of Active Social Media Use and Non-Loneliness Constructs



An Egger's regression test was significant ($\bar{z}$ = 0.07 [SE= 0.02], 95% CI [0.03, 0.10], z = 3.89, p < .001). Residual heterogeneity was low (Q[8] = 9.82, p = .28, suggesting that the estimated residual between-study variance was negligible. The low I^2 result indicates the remaining

variability is due to sampling error. The predictor (R^2 = .99) accounts for a large amount of heterogeneity.

Moderation Analyses

Several moderation analyses were conducted for both PSMU and ASMU studies to evaluate the significance of age, SC construct, and gender. Despite planned moderation analyses of socioeconomic status, digital literacy, and platform type, there were not sufficient studies to run meaningful analyses. For an in-depth assessment of results, see Appendix E.

Age as Moderator. To evaluate differences in SC across the lifespan, studies were categorized into age groups, including "Youth" (10-17), "Emerging Adults" (18-29), "Middle Adults" (30-64), "Older Adults" (65 and older), and "Lifespan" for studies which included age ranges beyond the scope of any predetermined group. No studies included youth ages 6 to 9. To reduce potential conflation of age groups, groups were designated by two different categorical variables; Age groups determined by the mean age reported in the study ("age_groupxmean"), and age groups determined by the age range reported in the study ("age_groupxrange"). There were (k = 5) studies which were identified as "Lifespan" studies when the reported age range was used to determine study age, and the age ranges included 18 – 72 (Dibb & Foster, 2021), 18 – 82 (Helm et al., 2022), 18 – 70 (Pennington, 2021), 18 – 78 (Santarelli & Krcmar, 2022), and 18 – 81 (Yue et al., 2024). The same studies were identified as "Middle Adult" when only the reported mean age was used, as the reported mean ages of these studies fell between 32.91 and 39.07. Less than half of the included studies (k = 11) reported only the M ages or the age ranges, and the majority of studies included both (k = 13); however, Lin and Longobardi (2025) reported the means and ranges on both of their samples. Several studies included a small percentage of individuals outside of these age ranges; for example, Pang (2020) included participants from 18

to 33 years old, with a mean age of 26.85 and SD of 0.97. In this case, Pang (2020) was considered an "emerging adult" study in both groupings. All mean- and range-based groupings, along with the reported means, SDs, and age ranges, are reported in detail in Appendix D.

Upon conducting analyses for PSMU studies, age group based on mean yielded non-significant results ($\bar{z}$ = -0.07 [SE= 0.03], 95% CI [-0.13, 0.00], z = -1.23, p = .05, Q_b[3] = 0.64, p = .89), suggesting that there is no evidence that age by mean explained the variability in effect sizes. This model demonstrated high heterogeneity (Q[13] = 63.81, p < .001, I^2=82.12%). The estimated variance of the true effect τ^2 = 0.01 (SE = 0.00), and the standard deviation of the true effect sizes τ = 0.10 indicate moderate variance. Between-study variance was low (R^2= .00), suggesting that the moderating variables do not explain the between-study heterogeneity. The ASMU model was also not statistically significant, ($\bar{z}$ = 0.09 [SE= 0.03], 95% CI [0.03, 0.16], z = 2.74, p = .01, Q_b[3] = 5.59, p = .13). Together, these results suggest age group, as defined by the means available to this study, did not significantly moderate the relationship between ASMU and SC. Heterogeneity was high (Q[16] = 170.73, p < .001, I^2=86.98%, τ^2 = 0.01 [SE = 0.00], τ = 0.10). Between-study variance was low (R^2= .15), indicating the moderating variable accounted for a small amount of variance between studies.

The second set of models examined age as a moderator using categorical age ranges. The PMSU model, which used emerging adults as the reference for the age range model, was non-significant ($\bar{z}$ = -0.05 [SE= 0.04], 95% CI [-0.13, 0.03], z = -1.29, p = .20, Q_b[2] = 0.1, p = .95). There were insufficient older adult and middle adult studies to include in this analysis. The ASMU model was also not significant ($\bar{z}$ = 0.09 [SE = 0.05], 95% CI [0.00, 0.18], z = 2.04, p = .04, Q_b [4] = 3.12, p = .54). These results suggest that overall, age range, as defined by this study, does not meaningfully moderate the relationship between ASMU and SC.

Gender as Moderator. Gender composition of the sample was examined as a potential moderator of the association between PSMU and SC outcomes using a mixed-effects meta-regression model. The analysis indicated that gender was not a statistically significant moderator ($\bar{z}$ = -0.08 [SE= 0.11], 95% CI [-0.30, 0.14], z = -0.72, p = .47, $Q_b(1)$ = 0.04, p = .84). The residual heterogeneity for this model was high ($Q(16)$ =78.83, p <.001, I^2 = 80.31%. The estimated variance of true effect sizes between studies was τ^2 = 0.01 (SE = 0.00), and the standard deviation of the true effect sizes, τ = 0.08, indicating low variance. Between-study variance was low (R^2= .00), suggesting that the moderators do not explain the between-study heterogeneity. These findings indicate that the association between PSMU and SC outcomes is consistent across samples with differing gender compositions, with no evidence that the strength of association varies as a function of gender.

The gender moderation analysis for ASMU yielded different results. The ASMU model was significant ($\bar{z}$ = -0.10 [SE= 0.09], 95% CI [-0.28, 0.08], z = -1.12, p = .26, $Q_b[1]$ = 4.6, p = .03), indicating that gender did significantly moderate the relationship. Heterogeneity was high for this model ($Q[20]$ = 204.71, p <.001, I^2 = 83.99%). The estimated variance of true effect sizes between studies was τ^2 = 0.01 (SE = 0.00), and the standard deviation of the true effect sizes, τ = 0.09, indicating variance. Between-study variance was low (R^2= .17), suggesting that the moderators explain none of the between-study heterogeneity. Subgroup analyses revealed that studies with higher proportions of female participants showed stronger associations with SC ($\bar{z}$ = 0.16 [SE= 0.02], 95% CI [0.13, 0.19], z = 9.18, p < .001). Although these findings are not particularly meaningful due to the high risk of ecological fallacy (Geissbühler et al., 2021), it is notable that SMU differences reflected at the individual study level and throughout the overall literature are also reflected in the present moderation analysis.

Construct Type as Moderator. A mixed-effects meta-regression examined whether the type of SC construct moderated the relationship between PSMU and SC. This analysis included "Loneliness," "Social Connectedness," and "Social Support," as there were not sufficient studies of "Belonging" or "Social Capital" to include. The test of moderators was significant ($\bar{z}$ = 0.02 [SE = 0.06], 95% CI [-0.11, 0.14], z = 0.26, p = .79, Q_b[3] = 8.31, p < .05), indicating there was evidence that effect sizes significantly differed across constructs. This is supported by the above subgroup analyses, where the restricted PSMU and SC model that included only loneliness was significant ($\bar{z}$ = -0.09, [SE = 0.02], 95% CI [-.13, -.04], z = -3.88, p < .001), but the other models, one restricting to only the SC construct and the other that excluded all constructs except loneliness, were not significant. The estimated residual heterogeneity was high Q(13) = 53.28, p < .001, and largely unexplained I^2 = 74.55%. The estimated variance of the true effect, τ^2 = 0.01 (SE = 0.00), and the standard deviation of the true effect sizes, τ = 0.08, indicate low variance. Between-study variance was moderately low R^2 = .29. In other words, the moderation analysis showed that constructs do significantly moderate the relationship between PSMU and SC.

Another mixed-effects meta-regression examined the moderating effect of construct type on ASMU and SC was conducted, including the constructs "Loneliness," "Social Capital," Social Connectedness," and "Social Support." Findings were significant ($\bar{z}$ = 0.31 [SE = 0.13], 95% CI [0.05, 0.57], z = 2.34, p < .05, Q_b [4] = 13.51, p < .05), indicating that there is evidence that effect sizes significantly differed across constructs. This finding is supported by the above subgroup analyses, which demonstrated a positive association between ASMU and SC when the loneliness construct was excluded from analyses ($\bar{z}$ = .15 [SE = 0.02], 95% CI [.11, .19], z = 7.63, p < .001), but was not significant when restricting to only the SC construct or the loneliness construct. Residual heterogeneity was higher in this model (Q[17] = 88.29, p < .001, I^2 =

79.56%) compared to the PSMU model. The estimated variance of the true effect, $\tau^2 = 0.01$ (SE = 0.00), and the standard deviation of the true effect sizes, $\tau = 0.08$, indicate variance. Between-study variance was moderate $R^2 = .42$. The overall results of this analysis suggest that not only does the construct type significantly moderate the relationship between ASMU and SC, but that loneliness specifically and significantly moderates the relationship between ASMU and SC.

Publication Bias

Visual inspection of the PSMU study funnel plots did not indicate clear asymmetry. Egger's regression test was not significant, $z = 1.31$, $p = .19$, suggesting no strong evidence of publication bias. Trim-and-fill analyses did not substantially alter the overall effect size, indicating that potential missing studies would be unlikely to meaningfully change conclusions. For the ASMU-focused analyses, visual inspection of the funnel plots did not indicate substantial asymmetry. Egger's regression test was non-significant, $z = 0.77$, $p = .44$, suggesting no strong evidence of publication bias. Trim-and-fill analyses did not meaningfully alter the pooled effect size, indicating that potential missing studies would be unlikely to substantially change the conclusions. Overall, results from the publication bias testing provide some assurances that the meta-analytic results are unlikely to be subject to publication/small study bias.

CHAPTER IV

DISCUSSION

The following section summarizes the findings from this systematic review and meta-analysis. Limitations of the current evidence on PSMU, ASMU, and SC, as well as moderating variables such as age, gender, and construct, will be discussed. Methodological limitations will also be presented. Finally, implications for policy and future research will be discussed.

Summary of Evidence

The present review aimed to fill key gaps in the current research on the association between SC and the SMU behaviors of PSMU and ASMU across the lifespan. Several random effects meta-analyses were conducted to examine whether there was a significant association between PSMU, ASMU, and SC (RQ1). Two comprehensive models, one assessing PSMU studies and one assessing ASMU studies, were conducted to examine the association between SMU type and all SC outcome measures. Both yielded small effect sizes, but significant results. Passive use, overall, is associated with lower connectedness, while active use is associated with higher connectedness. The small magnitude of the mean effect size in each model may be due to individual study sample sizes influencing overall means. For example, as discussed previously, only 4 of the 22 effect sizes included in the ASMU model were negative, and of these, 3 had large sample sizes, ranging from n = 1188 to n = 2828 (Keum et al., 2022; Frison & Eggermont, 2020; Wang et al., 2018), which likely lowered the overall mean effect. More importantly, the overall analysis revealed that 18 studies reported positive effect sizes, and of these, 11 studies reported CIs that did not surpass zero. This indicates that there is evidence in the literature that active use is associated with SC. Furthermore, the large number of included studies published between 2015 and 2025 suggests that this is an area of growing interest in the research.

However, the small magnitude of the mean effect size for both the PSMU and ASMU models may also be due to the included constructs. For example, in the PSMU model, 2 of the 5 positive effect sizes were from the only two studies included in the present review that measured SC using the Social Connectedness Scale: Rothschild and Weissbrod (2015) and Santarelli and Krcmar (2022). Twelve studies reported 13 negative effect sizes (Lin & Longobardi, 2025 contributed 2 effect sizes), and of these, 5 maintained CIs that did not surpass zero: Matook et al. (2015), Taylor et al. (2024), Pennington (2021), Keum et al. (2022), and Lin and Longobardi (2025). This suggests that there is evidence in the literature of a consistent relationship between passive use and lower connectedness. In the ASMU model, all four of the negative effect sizes came from studies that assessed loneliness, rather than any other SC construct. Together, the PSMU and ASMU model results suggest that there may be underlying differences between SC constructs, distinguishing loneliness and potentially SC from the other included SC constructs (e.g., belonging and social support). As evidenced by the studies included in the analysis, much of the previous research has tested the association between PSMU and loneliness, with findings typically confirming a positive relationship (Appel et al., 2016; Verduyn et al., 2017). The present findings are congruent with much of the previous research showing associations between P/ASMU and SC (e.g., Burke, 2025, Deters & Mehl, 2013, Hunt et al., 2021).

When analyses were restricted to studies directly measuring SC, neither PSMU nor ASMU demonstrated significant associations. Only $k = 2$ studies used SC-specific measures. For PSMU, the mean effect was 0.09 95% CI [-0.01, 0.19], Rothschild and Weissbrod (2015) reported an effect of 0.04, 95% CI [-0.14, 0.22], and Santarelli and Krcmar (2020) reported an effect of 0.11 [-0.00, 0.23]. In the ASMU model, the overall effect was 0.13, 95% CI [-0.08, 0.34]. Rothschild and Weissbrod (2015) reported an effect size of 0.01 95% CI [-0.17, 0.19],

while Santarelli and Krcmar (2020) reported an effect size of 0.22 95% CI [0.11, 0.34]. Although these results were not particularly meaningful due to the low rate of studies testing SC specifically, the findings contradict previous research, which has found direct, positive associations between SC and ASMU (e.g., Köbler et al., 2010). Furthermore, findings highlight several important issues. First, there is a lack of research on SC and SMU utilizing SC-specific measures such as the Social Connectedness Scale. Many studies that appeared relevant in initial screening were excluded in the full-text review stage for not exploring SC outcomes. Second, researchers have continued to evaluate SMU through negative bias, which is reflected in the present review as 17 of 24 included studies focused on loneliness as an outcome. While loneliness is a risk factor for vulnerable populations (i.e., older adults; World Health Organization, 2022) and therefore a relevant focus in studies of SMU, it does not discount the importance of testing potential protective factors. Third, the low rate of included SC-specific studies highlights a lack of interest in testing global SC. Some of the excluded studies tested only online-SC. Although valuable for exploring online experiences and moment-to-moment feelings during use, there is considerable research demonstrating that online experiences bleed into real-world feelings (Appel et al., 2016; Hunt et al., 2018), which highlights the importance of capturing global psychosocial experiences. While dichotomizing SC by online or in-person environments may provide useful information about where people find community and how users feel while using SM (Bailey et al., 2017), it does not necessarily provide information about how SMU relates to overall feelings of connectedness.

Due to the high rate of studies reporting measures of loneliness (e.g., UCLA Loneliness Scale; Russell, 1996), two additional meta-analyses were conducted to test the associations between loneliness and P/ASMU. PSMU showed a small but consistent negative association

with loneliness, with an overall effect of -0.09, 95% CI [-0.13, -0.04]. Since loneliness was reverse coded such that high scores indicated less loneliness, this finding suggests that passive use is indeed associated with higher levels of loneliness. Of the $k = 14$ studies included $k = 5$ maintained CIs below zero. Only Helm et al. (2022; $\bar{z} = 0.01$, 95% CI [-0.05, 0.07]) and Rothschild and Weissbrod (2015; $\bar{z} = 0.04$, 95% CI [-0.14, 0.22]) reported effect sizes greater than zero. It is possible that the large sample size ($n = 1147$) from Helm et al. (2022) influenced the overall mean, resulting in a smaller overall effect size. These findings align with previous research and theories emphasizing either direct associations between PSMU and loneliness or indirect associations via social comparison and passive consumption, which have been shown to exacerbate perceived social deficits (Cheng et al., 2023; Lewin, et al., 2023). ASMU was not significantly associated with loneliness overall, but several studies did report significant findings, including Keum et al. (2022; $\bar{z} = -0.14$, 95% CI [-0.18, -0.10]) and Yue et al. (2024; $\bar{z} = -0.13$, 95% CI [-0.21, -0.05]). The evidence of small-study effects suggests that previously reported positive associations between ASMU and loneliness may be inflated.

This finding complicates theoretical perspectives that frame active engagement as uniformly beneficial for social well-being but also calls for further assessment. As discussed prior, many researchers have theorized that active engagement would decrease loneliness (Nowland et al., 2018), grounding their work on theories such as the Rich-Get-Richer theory (Manago et al., 2012). However, ASMU is defined as any interactive behaviors, public and private, which may not accurately capture the nuances of user behaviors. For example, users that regularly post on their social medias (a “public” interaction) may garner different benefits than those who message individuals directly (a form of private interaction). Without clear distinctions

between the types of active use, researchers risk losing meaningful information about all behaviors.

When loneliness was excluded and analyses focused on other indicators of social connection, no association was found between PSMU and SC, reinforcing the conclusion that its effects are not broadly generalizable across all forms of SC. On the other hand, ASMU demonstrated a positive association, suggesting there is a relationship between interactive behaviors and certain aspects of social connection. Considering the other analyses in this review, including the significant and positive result from the ASMU model that included all SC constructs and the subgroup analyses, which found loneliness was a significant predictor at the conditional level, it is likely that the significant association between ASMU and SC is more generalizable. However, this effect should be interpreted cautiously, as there was evidence of asymmetry, and effect sizes were small. For example, Vogel et al. (2024) reported a small mean effect size of 0.09, 95% CI [0.06, 0.11]. The presence of heterogeneity in this analysis points to differences in populations and contexts, which should be considered when interpreting results.

A series of mixed-effects meta-regression models were conducted to examine the potential moderating effects of age on the association between P/ASMU and SC (RQ2). A primary focus of this review was to evaluate whether age groups moderated differences in SC outcomes for various age groups. The hypothesis that age would moderate the strength of association between SMU type and SC outcome was grounded in user data (e.g., age group use patterns, user motivations; Cotten et al., 2012; Ellison et al., 2007; Perrin, 2015; Vitak, 2012), as well as theory (e.g., Life Course Theory). Yet results indicated that age did not significantly moderate the association between SMU and SC overall. First, it is possible that the relationship between SMU and SC is relatively consistent across the lifespan. This would contradict

developmental theories that emphasize age-specific vulnerabilities and social needs (Macmillan, 2005). This possibility seemingly contrasts with descriptive data, which shows not only differences in how younger and older generations use SM, but in the motivations and reasons for using SM across age groups (Cotten et al., 2012; Ellison et al., 2007; Perrin, 2015; Vitak, 2012). A more plausible explanation is that the current literature has not sufficiently explored outcomes for specific, developmentally defined age groups, for example, emerging adults or older adults. This is likely due to research design limitations, such as using convenience samples, as well as a lack of clear, comprehensive reporting on the age frequencies and compositions of studies, both of which presented limitations for the present analysis. However, it is worth considering that emerging adults did significantly moderate the association between ASMU and SC at the conditional level, regardless of whether age was categorized by mean or range.

Two additional mixed-effect meta-regression models were conducted to examine the potential moderating effects of gender (RQ3). Similarly, gender composition did not meaningfully account for differences in the PSMU model, indicating that these associations are not strongly patterned by gender composition at the study level. However, the ASMU model was significant, indicating that gender did significantly moderate the relationship. Specifically, studies with higher proportions of females had significantly stronger associations. Previous research has highlighted a key difference in male and female ASMU, specifically in regard to using SM to develop new relationships (males) or to maintain existing relationships (females). Although there are likely other factors that may contribute to the conditional nature of this moderation, future research should consider exploring whether there are significant differences in SC outcomes for individuals who use SM to begin or maintain relationships. However, both

PSMU and ASMU gender moderation analyses must be interpreted with caution (Geissbühler et al., 2021).

A final series of analyses tested the moderating role of SC constructs (RQ4). In contrast with the previous moderation analyses, construct type emerged as a significant moderator, indicating that the nature of the SC outcome substantially shaped observed relationships. Although one might assume this finding supports the need for a conceptual separation of the included types of SC (i.e., social support vs. belonging), there are several explanations. First, these findings suggest that there are discrepancies between the scales used within the literature. As seen in several of the included studies, many researchers forgo comprehensive scales and elect to use subscales, short-form scales, or variations of scales (see Appendix D for a comprehensive list of included measures). Researchers often cite time constraints and participant survey fatigue as a primary reason for utilizing short-form scales (Lantos et al., 2023), however, careful consideration must be given to whether partial scales are able to comprehensively capture complex psychosocial experiences such as loneliness. The conceptualization of constructs also requires careful consideration. Despite the theoretical conceptualization of loneliness as the opposite of SC (Jordan, 2023), there are clear discrepancies between this theoretical perspective and the operationalization and measurement of loneliness. While some authors from the included studies identified and distinguished loneliness scores into the subcategories of "social loneliness" and "emotional loneliness," allowing the present review to test social loneliness alone, most provided in discriminant composite scores of loneliness (see Appendix D). When the ASMU model was tested for the moderating effect of the construct, overall findings were significant, and studies that used the loneliness construct showed stronger associations with SC.

Limitations

The present review has several limitations. First, the exploration of SMU through broad, observable external behaviors (i.e., "liking," or "lurking") does not capture the nuances of internal behaviors such as social comparison. Potential moderating variables such as user motivations, user context, user digital literacy, and time spent engaging in passive or active behaviors were not explored. Variability in how existing research defines and measures PSMU and ASMU may have also contributed to mixed findings in the observed effect sizes (Orben, 2020). Although the present study sought to document how each included study operationalized PSMU and ASMU and to account for inconsistencies where possible, many studies did not provide sufficiently precise definitions. This lack of measurement standardization limits the comparability of findings across studies. Furthermore, data was collected through self-reports rather than platform metrics. Social desirability bias and inaccuracies in reporting time spent or activity on SM are both limitations, as participants may consciously or unconsciously misrepresent their activity, affecting the accuracy of results (Aalbers et al., 2019; Gregory et al., 2023; Hunt et al., 2021; Taylor et al., 2024). This is of particular note as previous research has found not only that participants consistently overestimate time spent on SM but may also report using platforms they did not actually use (Boyle et al., 2022). Habitual behaviors (e.g., checking phones sporadically throughout the day) may make participants especially prone to misreporting. Retrospective data collection, particularly regarding SM behavior prior to the pandemic or at earlier life stages, risks introducing recall bias, which can affect the validity of reported trends or associations (Dziura et al., 2023). Participants' awareness of being observed for a SM or mental health study can itself influence their responses and SM behavior, potentially introducing bias to the study's findings (Deters & Mehl, 2013).

Relatedly, construct definitions of SC varied substantially across studies. Although subgroup analyses and moderation analyses were conducted to examine study-to-study operationalization differences, it was clear that even studies focused on shared constructs may have encountered problems. For example, $k = 7$ of the $k = 18$ studies measuring loneliness utilized shortened versions of the 20-item UCLA Loneliness scale (Dibb & Foster, 2021; Keum et al., 2022; Matook et al., 2015; Pennington, 2021; Wu et al., 2024; S. Yang et al., 2021; Zhao et al., 2023) ranging from 3- to 11-item scales, or reported on either emotional loneliness or social loneliness scores rather than both (e.g., Frison & Eggermont, 2020). Composite scores of loneliness that utilized shortened or partial measures likely conflated SC outcomes with other types of relational or individual outcomes. Such variability in construct measurement likely contributed to the high heterogeneity observed and complicated the interpretation of pooled effect sizes. Ideally, studies exploring the experiences of loneliness would measure and report the various subjective and relational aspects of the construct (i.e., romantic loneliness vs. social loneliness). Although it is theoretically appropriate to group constructs of connectedness together, results indicate that there are likely too many differences in operationalization to do so effectively. Some studies reported multiple SC constructs, such as social support and loneliness (McNamara & Heimberg, 2023; Rothschild & Weissbrod, 2015; Santarelli & Krcmar, 2020; see Appendix D for a detailed summary), and to prevent violation of independence of observation, the construct considered most similar to SC based on previous research (Kelley et al., 2025) was selected for inclusion. Although subgroup analyses often mitigated this limitation, it is worth mentioning the potential for researcher bias to influence analyses and therefore findings.

The lack of longitudinal data presented a limitation for the present study. Cross-sectional studies do not account for the potential directionality of associations or whether participants

experienced changes in ASMU, PSMU, or SC over time. Another limitation of the included studies was that many relied on convenience sampling, often drawing from university populations that are disproportionately female and White. This limits the generalizability of findings to more diverse populations and raises concerns about representativeness.

Furthermore, the lack of studies focused on specific age groups, followed by a lack of specificity in reported participant age ranges and means, contributed to the limitations of the moderation analyses. SM use and engagement differ substantially across age groups (e.g., 18–24-year-olds vs. 65–85-year-olds; Perrin, 2015), and aggregating across these groups may obscure meaningful differences in how SM relates to SC. Although attempts were made to reduce these limitations by creating two different age variables (reported age mean and age range), the lack of data, either by study design or reported information limits generalizability of results. Most studies did not differentiate between specific platforms (e.g., Facebook vs. Instagram) or test platform-based differences on user outcomes. This lack of contextual and behavioral specificity limits the ability to draw nuanced conclusions about how and why SMU may influence SC outcomes (Taylor et al., 2024). The results of the moderation analyses for both age groupings must be interpreted cautiously, as there were several limitations.

Implications for Future Research

The present systematic review and meta-analysis highlights several important directions for future research on SMU and SC. Across both ASMU and PSMU, findings indicated small and inconsistent effects, accompanied by substantial heterogeneity that was largely unexplained by the moderators examined (i.e., age, gender, and construct type). These patterns highlight the need for greater conceptual precision and methodological rigor to better understand when and how SMU type relates to SC. Future research should move beyond treating SMU as binary and

instead examine the specific mechanisms through which different behaviors may influence social outcomes. Active use encompasses a range of distinct activities, including direct messaging, commenting, posting content, and interacting with others' posts (Verduyn et al., 2017), all of which likely vary in the capacity to foster social connection (Memon et al., 2018; Shannon et al., 2022). Direct interpersonal exchanges may more effectively facilitate perceptions of support and belonging than more broadcast-oriented behaviors (Gazi et al., 2024). Disaggregating these forms of engagement will enable a more precise understanding of the pathways through which SMU may contribute to SC.

The substantial heterogeneity observed across studies highlights the importance of identifying more refined contextual moderators. Although the moderation analyses testing age and gender were underpowered, there was some evidence that studies with higher proportions of females and studies focused on emerging adults show stronger associations between ASMU and SC. These variables were examined at relatively broad levels and may not capture meaningful variation in user experiences. Future research should consider more nuanced moderators, including platform-specific features, cultural context, and norms surrounding online interaction. Such factors are likely to shape both how individuals engage with SM and the extent to which these interactions translate into meaningful social outcomes. More rigorous tests of moderators, specifically utilizing individual participant data (IPD) would yield more meaningful results. Aggregate-level data of participant age and gender are underpowered, and IPD meta-analyses would not only support filling a gap in the literature but also provide information about the potential differences in effects between age groups and genders.

As with most correlation-based research, this review highlights the critical need for research designs that can address issues of directionality and causality. The predominance of

cross-sectional studies in the existing literature limits the ability to determine whether SMU influences SC or whether individuals with differing levels of social connection engage with SM in distinct ways. Longitudinal designs are essential for clarifying temporal relationships, while experimental approaches can isolate specific mechanisms and establish causal effects. A focus on experimental research designs would also strengthen the findings of future studies, providing a stronger evidence base for both theory and practice.

Future research should more clearly distinguish between different dimensions of SC, particularly the distinction between emotional and structural aspects of connection. The present findings indicate that ASMU is positively associated with outcomes such as social support, belonging, and social capital, but not with loneliness. This divergence suggests that loneliness may represent a qualitatively distinct construct, reflecting deeper emotional experiences that are not readily influenced by online interaction. Greater clarity and consistency in the operationalization of these constructs will improve comparability across studies and reduce conceptual ambiguity in the literature. Future work should increasingly focus on more precise behavioral measurement, context-sensitive moderators, and rigorous research designs. Such efforts will be critical for developing a more comprehensive understanding of the conditions under which SM use contributes to meaningful SC.

Conclusion

Overall, the present meta-analyses revealed that effect sizes linking SMU to SC outcomes were small and often non-significant, with substantial variability across studies. Patterns differed between passive and active use, with ASMU demonstrating a small but positive association with certain forms of social connection, particularly social support, belonging, and social capital. However, these effects were not consistent across all constructs and were notably

absent for loneliness, underscoring important distinctions among SC outcomes. The high degree of heterogeneity observed suggests that these relationships are not uniform and are likely influenced by factors not captured in the present analyses, as neither construct type nor age significantly explained variability in effect sizes. Taken together, these findings indicate that there is no simple or universal association between SMU and SC and highlight the importance of conceptual precision in distinguishing between different dimensions of social connection, particularly given the limited practical magnitude of observed effects. Considering the lack of clear, consistent, and comparable research assessing the associations between PSMU, ASMU, and SC outcomes, researchers and policymakers alike should remain cautious about citing SC outcomes as reasons to implement SMU restrictions, particularly for youth, who may or may not experience greater SC with SMU.

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APPENDIX A

CODING MANUAL

The Association Between Passive and Active Social Media Use and Social Connectedness Across the Lifespan: A Systematic Review and Meta-Analysis

Coding Manual

Last updated: April 9, 2026

Eligibility Criteria

Study Design

1. Studies must be quantitative in nature or include quantitative aspects such that effect sizes are reported or can be calculated. Qualitative studies are not eligible, nor are review studies, including other meta-analytic or systematic reviews, scoping or rapid reviews, or any other type of review or narrative study.

Research Design

2. Studies must include at least one passive or active social media use group to be included. Pre-experimental, quasi-experimental, and randomized controlled trials are eligible, but must include at least one group that engages in passive or active social media use.

Social Media Platforms

3. Studies must differentiate between social media and screen time, media use (e.g., videogaming), and non-social media site usage to be included. If study includes non-social networking sites or apps (e.g., Quora, WhatsApp) data must be disaggregated such that social media use can be analyzed separately.
4. Studies must include social media platforms and must not include non-social media platforms. The following is a list of social media platforms that are and are not eligible for the present review:

✓ Accepted		⊖ Not Accepted
Facebook	4chan	WhatsApp
Instagram	StumbleUpon	Yelp
Gram	Omegle	Quora
TikTok	Tumblr	Skype
YouTube	MySpace	Zoom
BeReal	Threads	
Discord	Bluesky	
Flickr	Vine	
LinkedIn	DeVine	
Pinterest	YikYak	
Reddit	Mastadon	
4chan	Lemon8	
StumbleUpon	WeChat	
Omegle		

Condition

5. Studies focused on overall social media use, frequency of use, intensity of use, problematic use, or probability of use are not eligible.
6. Studies must differentiate between passive and active use.

Outcome Measures

7. Studies must include at least one measure of social connectedness. “Social connectedness” may be referred to as social relationships, social cohesion, social support,

social networks, social belonging, social isolation, loneliness, quality of life, or another related construct.

8. The social connectedness measure must be an experience of overall social connectedness, not restricted to specific settings. Measures that measure online-only social connectedness do not meet the criteria. Examples of eligible and non-eligible social connectedness include, but are not limited to, the following:

✅	Hemmingway Measure of Adolescent Connectedness (McWhirter & McWhirter, 2011)
✅	The Revised Social Connectedness Scale (Lee et al., 2001)
✅	The Watts Connectedness Scale (Watts et al., 2022)
✅	The Multidimensional Scale of Perceived Social Support (Zimet et al., 1988)
✅	The Sense of Belonging Instrument (Hagerty & Patusky, 1995)
✅	The UCLA Loneliness Scale (Russell et al., 1978; Russell, 1996)
✅	The Children's Loneliness and Social Dissatisfaction Scale (Asher et al., 1984)
✅	The Basic Psychological Needs Satisfaction Scale (Ryan & Deci, 2000).
✅	The Social and Emotional Loneliness Scale for Adults (DiTommaso & Spinner, 1993)
✅	PALS Perth A-Loneliness
⛔	The Beck Depression Inventory (Beck) ❌ does not measure SC
⛔	Columbia-Suicide Severity Scale ❌ does not measure SC
⛔	WHO-5 mental wellbeing scale
⛔	General Health Questionnaire (GHQ-12).
⛔	Rosenberg Self-Esteem Scale (RSES;
⛔	the Iowa-Netherlands Comparison Orientation Scale (INCOM)
⛔	Kessler 6-item scale (K6),
⛔	Warwick Edinburgh Mental Wellbeing Scale (WEMWBS)

Publication Date, Type, and Source

9. Studies must be published during or after 1997.
10. Studies must be published in English.
11. Participants must be 6 years of age or older.

Full-Text Coding

Study Level

The following reports all study level information. Any cased in which there are multiple reports using the same study data must be evaluated to identify which report is most comprehensive, and that report will be used. Any cases in which a manuscript reports multiple studies, each study will be handled as a separate report, and assigned an independent ID.

Study Identifiers

[ID]	Number assigned to each effect size.
[coder]	Coder name.
[cdate]	Date of original coding (mm/dd/yy).
[mdate]	Date of coding modifications (mm/dd/yy).

Study Details

[author]	Author(s) of study.
[year]	Year of study publication.
[title]	Title of the study.
[pubtype]	Type of publication: 1. Journal article 2. Thesis or dissertation 3. Technical report 4. Conference report 5. Book 6. Book chapter 7. Other (specify)
[country]	The country or countries where the study was conducted.
[samplingmethod]	Method used to recruit participants: 1. Randomized 2. Convenience sampling Other (specify)
[samplesetting]	Reported sample setting or recruitment setting: 1. University 2. School (k-12) 3. Healthcare 4. Mental health care (outpatient) 5. Mental health care (inpatient) 6. Social services or non-profit 7. Community 8. Graduate students 9. Other (specify)
[smplatform]	List of social media (SM) platforms included in the study. If not specified, list NA)
[smdescrip]	Description of how the authors defined SM.

[apdescrip]	Description of how the authors describe active social media use (ASMU) and passive social media use (PSMU).

Study Methods

[design_type]	List the type of study design: 1. Pre-experimental (no control group) 2. Quasi-experimental (control but not randomized) 3. Randomized controlled trial
[design_time]	List the type of study design (length): 1. Cross-sectional 2. Longitudinal 3. Both
[timepoint]	Timepoints included in the study: 1. Baseline 2. Follow-up 1 3. Follow-up 2 4. Other (specify)
[funum]	Number of follow-ups assessed.
[sc_measure]	Primary measure used to assess social connectedness (SC) or related construct.
[sc_add_measure]	Additional measures used to assess SC construct. If SC was measured using Social Connectedness Scale, but loneliness was also measured using the UCLA Loneliness Scale, list "UCLA Loneliness Scale" here.
[ap_measure]	Measure used to assess passive and/or active social media use (list "researcher developed" if not pre-existing scale).
[ap_question]	Researcher developed questions used to assess passive and/or active social media use.

Study contributions

[contribution]	Quotes, summaries, page numbers, and notes on study-level contributions.
[limitations]	Quotes, summaries, page numbers, and notes on study-level limitations.
[fd]	Quotes, summaries, page numbers, and notes on suggested study-level future directions.
[notes]	Any additional study-level notes.

Quality Assessment

Data collection methods

[collection]	Data collection methods used in studies (list all relevant methods): 1. Self-report surveys 2. Assessment 3. Observations 4. Other (specify)
[att_post]	Percent attrition at post (people who dropped)
[att_fu1]	Percent attrition at follow-up 1 (baseline to post)
[att_fu2]	Percent attrition at follow-up 2 (baseline to follow-up)
[evidence]	Type of measures used (list all relevant): 1. Existing measure/scale 2. Researcher-developed questionnaires
[rdq]	If researcher developed, what were the questions asked (list, and specify if not reported)
[sponsor_rel]	Did the authors report any sponsorship or study funding? 1. No 2. Yes 3. Unknown

Participant Characteristics

[permale]	Percent of participants who identify as male.
[perfem]	Percent of participants who identify as female.
[pernon]	Percent of participants who identify as neither cis male nor cis female.
[m_age]	Mean age of participants.
[sd_age]	Standard deviations of participant ages.
[r_age]	Participant age range.
[sesstatus]	Any data on socioeconomic status information for participants.
[diglit]	Any information on digital literacy of participants, including measures, reported data, or findings.
[rec_size]	Reported number of participants recruited.
[inc_size]	Reported number of participants included in analysis.
[pass_size]	Reported number of participants in the passive group.
[pass_mani_size]	Reported number of participants in the manipulated passive group (e.g., those engaging in PSMU more than usual)
[act_size]	Reported number of participants in the active group.
[act_mani_size]	Reported number of participants in the manipulated active group (e.g., those engaging in ASMU more than usual)
[control_size]	Reported number of participants in the control group.

Effect Size Coding

Cross-sectional Studies

[page]	Page number of effect size
[corr_measure]	The measure used for the reported SC correlation (e.g., Social Connectedness Scale, UCLA Loneliness Scale, etc.).
[r_passive]	The reported correlation (r) or standardized coefficient (b) from regressions for passive use.
[pass_sig]	Reported p-values for passive effect sizes
[r_active]	The reported correlation (r) or standardized coefficient (b) from regressions for active use.
[act_sig]	Reported p-values for active effect sizes.
[r_control]	The reported correlation (r) or standardized coefficient (b) from regressions for control groups.
[esprob_cross]	Notes on any problems with coding the effect size.

Longitudinal Studies

[a_esfu]	Timing for the follow up (e.g., time point 2, 3, etc.) for active use.
[a_esmeas]	The measure used for the reported SC correlation (e.g., Social Connectedness Scale, UCLA Loneliness Scale, etc.).
[a_escorr]	Correlation between time 1 and time 3 measures for active use.
[a_esn]	Number of participants included in analysis for active use.
[p_esfu]	Timing for the follow up (e.g., time point 2, 3, etc.) for passive use.
[a_esmeas]	The measure used for the reported SC correlation (e.g., Social Connectedness Scale, UCLA Loneliness Scale, etc.).
[a_escorr]	Correlation between time 1 and time 3 measures for passive use.
[a_esn]	Number of participants included in analysis for passive use.
[esprob_long]	Notes on any problems with coding the effect size.
[es_notes]	Any additional notes on effect size coding.

APPENDIX B

SCREENING INSTRUCTIONS

The first goal is to eliminate studies that clearly do NOT meet criteria. Some criteria will be difficult to identify during the title/abstract screening (e.g., definitions of social media, sample demographics, measures used). Do not waste time on each abstract - Reject any that clearly do not meet criteria (e.g., non-English, qualitative, not about social media, not about mental health or connectedness)

Title and Abstract Screening

Software Instructions:

1. Log in to your **Rayyan.ai** account and click on the project
2. Once open, there will be several tabs toward the top left of the website - click on "Screening"
3. There will be a list of the articles in a left-hand column - at the top of that there are three horizontal bars - click that and "sort" the articles by "author" and "A-Z."
4. Scroll down to your assigned author group and begin screening. Make sure you are screening your assigned section! If you accidentally overlap with someone else, it will waste your valuable project time :)
    - For example, if your assigned group is N-P, scroll down to the "N's" and begin screening.

Assigned Sections:
Xiaoqi: A-D, Q-T
Jessica: E-H, Y-Z
Ethan: I-L
Vivian: M-P
Aubrey: U-W

Screener Instructions:
Please carefully review the **full title and full abstract** before making any decisions. The exception to this rule is if the *title* states the article is:

1. **A review article**
    - Such as a scoping review, systematic review, meta-analysis, etc.
2. **An *exclusively* qualitative study**
    - For example, "What Factors Contribute to the Motivation of Adults Who Stutter to Continue Their Treatment? A Qualitative Study"
3. **About medicine, biology, or disease**
    - For example, "High Prevalence of Sexually Transmitted Infections, and High-Risk Sexual Behaviors Among Indigenous Adolescents of the Comarca Ngäbe-Buglé, Panama,"
4. **Clearly unrelated to social sciences**

- For example, “Self-powered ultra-flexible electronics via nano-grating-patterned organic photovoltaics”

If you are unsure of whether the article should be included or not, please review the entire article a second time. If you are still unsure, please take a not in the Software explaining the reason for your uncertainty (i.e., measures used, definitions provided, type of analysis used or data reported).

Some terms will be highlighted in green or red. This is to help make reviews more efficient, but please do not rely solely on these highlights to make your decision! The presence of green or red highlights does not indicate immediate inclusion or exclusion.

Screener instructions for Full-Text Screening

Software Instructions
Log in to your account

1. and click on the project
2. Once open, there will be several tabs toward the top left of the website. Last time, you hit the “Screening” tab. This time, you will hit the “**Full-Text Screening**” tab.
3. All of the articles will be listed
4. Scroll down to your assigned author group and begin screening. Make sure you are screening your assigned section.
    - For example, if your assigned group is N-P, scroll down to the “N’s” and begin screening.

Assigned Sections:

Aubrey	Aalbers - Gann Turska-kawa - Wang & Mascoda
Vivian	Gao - Lemus, Wang (Wang, Zhijun, Anderson, Terry, Chen, Li) - Wu & Macy
Xiaoqi	Lepkowska - Nimrod Wu Zheng et al. - Yu Ping
Jessica	Nisar - Treitel Yuxiang - Zhu Dong Plus 4 no author articles

Roughly 75 articles per screener

Screening Instructions

At this stage, our goal is to review any articles that made it past Phase One, and see if after reading the full text, we think the article should still be included. **We are not yet collecting data.** Most studies violating Study Design, Year, Language, and Population criteria will have been rejected already. The primary focus at this stage will be on the Measures, Population, and Social Media Definition (although we should still keep an eye out for any other criteria violations we missed in the first stage!)

Focus first on the **introduction, methods, and results** sections of each article. You'll need to have a good idea of the following:

1. How social media is defined (e.g., what apps or websites are included?)
    1. If Active and Passive Use is differentiated/defined
    2. Remember, a study may not use the term "active" or "passive," so check what exactly participants are doing in their social media use.
2. Sample demographics
3. Outcome measures used

For each rejection, you **must label the reason for exclusion.** This will be reported in the final dissertation/manuscript. Here is an example:

1. The article is about depression in youth who are part of the Youth Socialist movement in Spain.
    1. You would label this as both **"Wrong Outcome"** (i.e., depression) and **"Wrong Topic"** (i.e., politics).
2. You **do not** need to list *why* you have labeled the article "Wrong Outcome" and "Wrong Topic," but you must label why it is ineligible for inclusion.

Some terms will be highlighted in green or red. This is to help make reviews more efficient, but please do not rely solely on these highlights to make your decision! The presence of green or red highlights does not indicate immediate inclusion or exclusion.

APPENDIX C. RISK OF BIAS TABLE

Study	Incomplete Data Handling	Outcome Assessment	Selective Reporting
Aalbers et al., 2019	L	H	U
Dibb & Foster 2021	L	H	L
Frison & Eggermont 2020	U	U	L
Helm et al. 2022	L	H	L
Keum et al. 2022	L	H	U
Lin & Longobardi 2025	L	U	L
Mao et al. 2023	L	U	L
Matook et al. 2015	U	H	L
McNamara & Heimberg 2023	U	U	H
Molaie & Fisher 2022	L	U	U
O'Brien et al. 2021	L	U	U
Pang 2020	L	H	L
Pennington 2021	L	H	L
Rothschild & Weissbrod 2015	L	U	H
Santarelli & Krcmar 2022	L	L	L
Sohn & Washington 2025	L	U	H
Taylor et al. 2024	L	U	U
Tobin et al. 2015	L	L	U
Vogel et al. 2024	L	L	H
Wang et al. 2018	U	L	U
Wu et al. 2024	L	L	L
Yang et al. 2021	L	H	L
Yue et al. 2024	L	H	L
Zhao et al. 2023	L	H	U

Notes. H = High risk, L = Low risk, U = Unclear

APPENDIX D

TABLE OF INCLUDED STUDIES

Author(s) (Year), Country	Sample size *N* M_{age}(*SD*) Grouping by Mean (Age Range) Grouping by Range	Outcome Measure (Description, Author) *Construct*	Social Media Use Type Effect size (Pearson's Correlation, *r*)	
			Passive Pearson's correlation	Active Pearson's correlation
Aalbers et al., (2019) Netherlands	125 20.44 (1.96) Emerging Adult (N/A) Emerging Adult	Researcher developed (12-item questionnaire including item for loneliness, loss of interest, fatigue, etc.) *Loneliness*	-0.03	
Dibb & Foster,(2021) UK	214 35.65 (15.10) Middle Adult (18 – 72) Lifespan	UCLA Loneliness Scale (8 – item version) *Loneliness*	-0.08	0.065
Frison & Eggermont, (2020) Belgium	1423 14.3 (1.43) Youth (12 – 19) Youth	De Jong-Gierveld & Kamphuls (1985) Loneliness Scale (Emotional Loneliness of 11-item version) *Loneliness*	-0.06	-0.055
Helm et al., (2022) U.S.	1147 37.47 (12.64) Middle Adult (18 – 82) Lifespan	De Jong Gierveld Loneliness Scale (3-items for Social Loneliness) *Loneliness*	0.01	0.02

Author(s) (Year), Country	Sample size *N* M_{age}(*SD*) Grouping by Mean (Age Range) Grouping by Range	Outcome Measure (Description, Author) *Construct*	Social Media Use Type Effect size (Pearson's Correlation, *r*)	
			Passive Pearson's correlation	Active Pearson's correlation
Keum et al., (2022) U.S.	2828 18.3 (N/A) Emerging Adult (17 – 25) Emerging Adult	Revised UCLA Loneliness Scale (3-item short-form, Hughes et al., 2004) *Loneliness*	-0.16	-0.14
Lin & Longobardi (2025) China	565 19.54 (1.15) Emerging Adult (18 – 27) Emerging Adult	Multidimensional Scale of Perceived Social Support (Zimet et al., 1988) *Social Support*	-0.14	0.18
Lin & Longobardi (2025) China - *Italian Sample*	425 22.03 (2.28) Emerging Adult (18 – 29) Emerging Adult	Multidimensional Scale of Perceived Social Support (Zimet et al., 1988) *Social Support*	-0.01	0.17
Mao et al., (2023) China	454 19.75 (1.33) Emerging Adult (18 – 27) Emerging Adult	The UCLA Loneliness Scale (Russell, 1996) *Loneliness*	-0.026	0.046
Matook et al., (2015) Australia	166 25 (N/A) Emerging Adult (N/A)	7-Item UCLA Loneliness Scale (Social Loneliness items; Russell, 1996) *Loneliness*	-0.235	0.0875

Author(s) (Year), Country	Sample size *N* M_{age}(*SD*) Grouping by Mean (Age Range) Grouping by Range	Outcome Measure (Description, Author) *Construct*	Social Media Use Type Effect size (Pearson's Correlation, *r*)	
			Passive Pearson's correlation	Active Pearson's correlation
McNamara & Heimberg (2023) U.S.	1091 19.36 (1.87) Emerging Adult (N/A) N/A	Revised UCLA Loneliness Scale (Peplua & Cutrona, 1980) *Loneliness*	-0.04	
McNamara & Heimberg (2023) U.S.	1091 19.36 (1.87) Emerging Adult (N/A) N/A	The Interpersonal Support and Evaluation List – Belonging Subscale (Cohen & Hoberman, 1983) *Belonging*	-0.01	
Molaie & Fisher (2022) U.S.	187 19.4 (1.80) Emerging Adult (18 – 25) Emerging Adult	Interpersonal Needs Questionnaire – 15 (Van Orden et al., 2012) *Belongingness*	0.062	
O'Brien et al., (2021) Canada	330 N/A (N/A) Older Adult 65 + Older Adult	Social Capital Scale (Erickson, 2011) *Social Capital*		0.183

Author(s) (Year), Country	Sample size *N* M_{age}(*SD*) Grouping by Mean (Age Range) Grouping by Range	Outcome Measure (Description, Author) *Construct*	Social Media Use Type Effect size (Pearson's Correlation, *r*)	
			Passive Pearson's correlation	Active Pearson's correlation
Pang (2020) Germany	298 26.85 (0.97) Emerging Adult (18 – 33) Emerging Adult	Researcher Developed Measure (Social Support in Home Country and Host Society; Pang, 2020) *Social Support*	0.095	0.18
Pennington (2021) U.S.	307 34.22 (12.01) Middle Adult (18 – 77) Lifespan	6-Item UCLA Loneliness Scale (Neto, 1992) *Loneliness*	-0.185	-0.06
Rothschild & Weissbrod (2015) U.S.	120 19 (N/A) Emerging Adult (N/A) N/A	Social Connectedness Scale – Revised (SCS-R; Lee et al., 2001) *Social Connectedness*	0.038	0.0065
Rothschild & Weissbrod (2015) U.S.	120 19 (N/A) Emerging Adult (N/A) N/A	The UCLA Loneliness Scale (Russell, 1996) *Loneliness*	0.042	-0.0095

Author(s) (Year), Country	Sample size *N* M_{age}(*SD*) Grouping by Mean (Age Range) Grouping by Range	Outcome Measure (Description, Author) *Construct*	Social Media Use Type Effect size (Pearson's Correlation, *r*)	
			Passive Pearson's correlation	Active Pearson's correlation
Rothschild & Weissbrod (2015) U.S.	120 19 (N/A) Emerging Adult (N/A) N/A	The National Institute of Health Adult Toolbox Social Relationship Scales (Cyranowski et al., 2013) *Social Support*	0.173	0.125
Santarelli & Krcmar (Santarelli & Krcmar, 2020) U.S.	295 39.91 (14.80) Middle Adult (18 – 78) Lifespan	Social Connectedness Scale - Revised (Lee et al., 2001) *Social Connectedness*	0.11	0.22
Santarelli & Krcmar (Santarelli & Krcmar, 2020) U.S.	295 39.91 (14.80) Middle Adult (18 – 78) Lifespan	The UCLA Loneliness Scale – Revised (Russell, 1996) *Loneliness*	-0.07	0.06
Santarelli & Krcmar (Santarelli & Krcmar, 2020) U.S.	295 39.91 (14.80) Middle Adult (18 – 78) Lifespan	Relatedness & Interaction Belonging Scale *Belonging*	0.17	0.16

Author(s) (Year), Country	Sample size *N* M_{age}(*SD*) Grouping by Mean (Age Range) Grouping by Range	Outcome Measure (Description, Author) *Construct*	Social Media Use Type Effect size (Pearson's Correlation, *r*)	
			Passive Pearson's correlation	Active Pearson's correlation
Sohn & Washington (2025) U.S.	87 N/A (N/A) N/A ("mostly" 25 – 44) Middle Adult	UCLA Loneliness Scale (Russell, 1996) *Loneliness*		0.1
Taylor et al. (2024) U.K.	288 20.75 (3.86) Emerging Adult (N/A) N/A	UCLA Loneliness Scale (Russell, 1996) *Loneliness*	-0.23	0.16
Tobin et al.(2015) U.S., Australia, U.K.	89 30.67 (11) Middle Adult (N/A) N/A	Measure of Perceived Belonging (Gonsalkorale & Williams, 2007) *Belonging*		0.3
Vogel et al.(2024) U.S.	5995 28.70 (N/A) Emerging Adult (N/A) N/A	Patient-Reported Outcomes Measurement Information System (PROMIS) Perceived Emotional Support Scale *Social Support*		0.087

Author(s) (Year), Country	Sample size *N* M_{age}(*SD*) Grouping by Mean (Age Range) Grouping by Range	Outcome Measure (Description, Author) *Construct*	Social Media Use Type Effect size (Pearson's Correlation, *r*)	
			Passive Pearson's correlation	Active Pearson's correlation
Wang et al. (2018) Belgium	1188 14.30 (1.43) Youth (N/A) N/A	De Jong-Gierveld & Kamphuls (1985) Loneliness Scale *Loneliness*		-0.03
Wu et al.(2024) China	684 19.11 (0.94) Emerging Adult (17 – 24) Emerging Adult	Multidimensional Scale of Perceived Social Support (Radloff, 1977) *Social Support*		0.182
Wu et al.(2024) China	684 19.11 (0.94) Emerging Adult (17 – 24) Emerging Adult	Multidimensional Scale of Perceived Social Support (Radloff, 1977) *Social Support*		0.006
Yang et al. (2021) China	201 69.84 (8.47) Older Adult (43 – 70) Middle Adult	6-Item Multidimensional Scale of Perceived Social Support (Zimet et al., 1988) *Social Support*	-0.134	0.23

Author(s) (Year), Country	Sample size *N* M_{age}(*SD*) Grouping by Mean (Age Range) Grouping by Range	Outcome Measure (Description, Author) *Construct*	Social Media Use Type Effect size (Pearson's Correlation, *r*)	
			Passive Pearson's correlation	Active Pearson's correlation
Yue et al.(2024) China	620 39.07 (11.01) Middle Adult (18 – 81) Lifespan	6-Item Multidimensional Scale of Perceived Social Support (Zimet et al., 1988) *Social Support*		0.12
Yue et al.(2024) China	620 39.07 (11.01) Middle Adult (18 – 81) Lifespan	3-Item UCLA Loneliness Scale (Hughes et al., 2004) *Loneliness*		-0.13
Zhao et al. (2023) U.S.	192 N/A (N/A) Emerging Adult (18 – 25) Emerging Adult	8-Item UCLA Loneliness Scale (Roberts et al., 1993) *Loneliness*	-0.03	0.05

APPENDIX E

RESULTS TABLE OF MAIN ANALYSES AND SUBGROUP ANALYSES

Passive Social Media Use and Social Connectedness Outcomes

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
-0.06	< .001	[−0.11, -0.01]	(17) = 79.91	79.52%	0.008	[-0.23, 0.12]	$\bar{z}$ = -0.07 (SE = 0,07), 95% CI [-0.21, 0.06], z = -1.14, p = .26 τ^2 = 0.01 (SE = 0.00), I^2 = 79.99%, R^2 = .00

Active Social Media Use and Social Connectedness Outcomes

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
0.09	< .001	[0.04, 0.14]	(21) = 206.23	87.84%	0.01	[−0.11, 0.29]	$\bar{z}$ = -0.01 (SE = 0.05), 95% CI [−0.12, 0.09], z = -0.30, p = .80 τ^2 = 0.01 (SE = 0.00), I^2 = 84.22%, R^2 = .20

Passive Social Media Use and Connectedness Only

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
.09	.07	[−.01, .19]	(1) = 0.44	0%	0.0	[-0.01, 0.19]	*Too Few Studies (k* = 2)

Active Social Media Use and Connectedness Only

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
.13	.24	[−.08, .34]	(1) = 3.94	74.61%	0.02	[-0.21, 0.46]	*Too Few Studies (k* = 2)

Passive Social Media Use and Loneliness Only

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
-.09	< .001	[-.13, -.04]	(13) = 47.74	70.24%	0.004	[-0.22, 0.05]	$\bar{z}$ = -0.08 (SE = 0.06), 95% CI [−0.19, 0.03], z = -1.35, p = .18 τ^2 = 0.01 (SE = 0.00), I^2 = 71.75%, R^2 = .00

Active Social Media Use and Loneliness Only

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
0.01	.64	[−0.04, 0.06]	(15) = 80.97	80.85%,	0.007	[−0.16, 0.19]	$\bar{z}$ = −0.13 (SE = 0.05), 95% CI [−0.22, -0.04], z = −2.74, p < .05 τ^2 = 0.00 (SE = 0.00), I^2 = 65.38%, R^2 = .53

Passive Social Media Use and Social Connectedness Excluding Loneliness

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
0.01	.74	[−0.06, 0.08]	(6) = 18.32	68.34%	0.01	[-0.15, 0.17]	*Too Few Studies (k* = 7)

Active Social Media Use and Social Connectedness Excluding Loneliness

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
.15	< .001	[.11, .19]	(9) = 22.71	50.31%	0.002	[0.06, 0.24]	$\bar{z}$ = 0.07 (SE= 0.02), 95% CI [0.03, 0.10], z = 3.89, p < .001 τ^2 = 0.00 (SE = 0.00), I^2 = 62.89%, R^2 = .99

Passive Social Media Use Age by Mean Moderation Analysis

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
-0.07	.05	[-0.13, 0.00]	(3)	82.12%	0.01		$\bar{z}$ = -0.10 (SE= 0.01), 95% CI [-0.28, 0.07], z = -1.19, p = .23 τ^2 = 0.01 (SE = 0.01), I^2 = 82.00%, R^2 = .00

Active Social Media Use Age by Mean Moderation Analysis

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
0.09	<.05	[0.03, 0.16]	(3) = 5.59	86.98%	0.01		$\bar{z}$ = 0.01 (SE= 0.69), 95% CI [-0.11, 0.13], z = 0.14, p = .89 τ^2 = 0.01 (SE = 0.00), I^2 = 84.56%, R^2 = .26

Passive Social Media Use Age by Range Moderation Analysis

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
-0.05	.20	[-0.13, 0.03]	(2) = 0.10	79.23%	0.01		$\bar{z}$ = -0.12 (SE= 0.09), 95% CI [-0.31, -0.31], z = -1.30, p = .19 τ^2 = 0.01 (SE = 0.01), I^2 = 76.86%, R^2 = .00

Active Social Media Use Age by Range Moderation Analysis

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
0.09	.05	[-0.00, 0.19]	(5) = 2.20	88.25%	0.01		$\bar{z}$ = -0.05 (SE= 0.12), 95% CI [-0.28, 0.18], z = -0.42, p = .68 τ^2 = 0.01 (SE = 0.01), I^2 = 85.03%, R^2 = .00

Passive Social Media Use Gender Moderation Analysis

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
-0.08	.47	[-0.30, 0.14]	(1) = 0.04	80.31%	0.01		$\bar{z}$ = -0.09 (SE= 0.12), 95% CI [-0.32, 0.15], z = -0.73, p = .47 τ^2 = 0.01 (SE = 0.00), I^2 = 80.84%, R^2 = .00

Active Social Media Gender Moderation Analysis

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
-0.10	0.26	[-0.28, 0.08]	(1) = 4.62	83.99%	0.01		$\bar{z}$ = -0.10 (SE= 0.09), 95% CI [-0.27, 0.08], z = -1.11, p = .27 τ^2 = 0.01 (SE = 0.00), I^2 = 83.12%, R^2 = .20

Passive Social Media Construct Moderation Analysis

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
0.02	.79	[-0.11, 0.14]	(3) = 8.31	74.55%	0.01		$\bar{z}$ = 0.03 (SE= 0.09), 95% CI [-0.13, 0.20], z = 0.40, p = .69 τ^2 = 0.01 (SE = 0.00), I^2 = 75.69%, R^2 = .22

Active Social Media Construct Moderation Analysis

b	*p*-value	95% CI	*Q(df)*	I^2	τ^2	95% PI	Egger's Regression Test
0.31	<.05	[0.05, 0.57]	(4) = 13.51	79.56%	0.01		$\bar{z}$ = 0.03 (SE= 0.09), 95% CI [-0.13, 0.20], z = 0.40, p = .69 τ^2 = 0.01 (SE = 0.00), I^2 = 75.69%, R^2 = .22

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