RESEARCH PAPER

Exploring the Effect of Social Media Addiction on Mental Health Through Sleep Quality: A Meta-Analytical Structural Equation Modeling Approach

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ABSTRACT

Objectives: This study aims to quantify the direct relationships among social media addiction, sleep quality, and depression, while also examining the indirect mechanism through which social media addiction affects depression via sleep quality. In addition, it explores the moderating roles of age and cultural context in shaping these associations.

Method: A systematic review of 207 studies in Scopus identified 32 eligible quantitative studies consisting of 45,667 participants. Effect sizes were synthesized using random-effects models, and mediation was tested through two-stage MASEM (Meta-Analytical Structural Equation Modeling) with 30 studies.

Results: The results showed that social media addiction was significantly associated with poorer sleep quality ($r = 0.237$, $p < .001$) and higher depression levels ($r = 0.32$, $p < .001$), with poor sleep quality also being significantly associated with greater depression ($r = 0.25$, $p < .01$). MASEM further confirmed sleep quality as a partial mediator of the association between social media addiction and depression ($\beta = 0.202$, $p = .012$), hence an effect that is both direct and indirect. In-depth moderator analyses revealed cross-cultural and age-related variations in findings, but publication bias was negligible.

Conclusions: These findings point out that sleep quality as a significant pathway through which excessive social media use develops symptoms of depression, hence the imperative for interventions in the field of digital well-being and healthy sleep as a means of reducing adverse mental health outcomes.

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INTRODUCTION

Sleep is a fundamental biological process, essential for cognitive function, emotional regulation, and physical health(Buysse, 2014).Adequate sleep has multifaceted benefits, including enhancing memory consolidation, (Stickgold, 2005) reducing free radicals (Inoué et al., 1995), clearing neurotoxic waste byproduct (Xie et al., 2013), and restoring mental and physical energy reserves (Harrington & Avidan, 2005). Throughout life, a person's health, social relationships, sleep quality, and other factors can affect quality of life and its various aspects (Netuveli & Blane, 2008; Ribeiro Do Valle et al., 2013; Tel, 2013; Zaninotto et al., 2009). Moreover, sleep quality plays an important role not only in maintaining good physical and mental health, but also in promoting normal functioning such as daily activities (Schubert et al., 2002; Vance et al., 2011).

The rapid industrialization, widespread artificial lighting, round-the-clock economic activity, and the advent of fast time-zone travel have collectively transformed human lifestyles in profound ways over the past 200 years. While these advancements in technology have unquestionably made our day-to-day lives easier, additionally, they introduced a novel phenomenon known as "circadian misalignment" (Rea et al., 2008; Vetter, 2018), which refers to the mismatch between the body's internal clock and external or social time, causing sleep and wake to occur at biologically inappropriate times and forming a core feature of circadian rhythm sleep–wake disorders (Baron & Reid, 2014; Sateia, 2014; Wittmann et al., 2006). Concurrently with rising concerns regarding sleep health, social media use has increased substantially over the past decade, especially among adolescents and young adults (Twenge et

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al., 2019). While social media platforms offer opportunities for communication and information sharing, excessive or maladaptive use often conceptualized as Social Media Addiction (SMA), has been associated with behavioral dysregulation, emotional dependence, and impaired psychosocial functioning (Andreassen et al., 2016; Kuss & Griffiths, 2017). Moreover, excessive social media use is associated with reduced sleep duration, prolonged time to fall asleep, and increased sleep disruptions (Cain & Gradisar, 2010; Whipps et al., 2018). Similarly, increased usage of platform like Facebook and Twitter has also been associated with poorer sleep quality (Bowler & Bourke, 2018). Furthermore, study observed that students who have symptoms of depression were about 2.5 times more likely to experience sleep problems (Guo et al., 2014).

A growing body of empirical studies has also documented a robust association between poor sleep quality and depressive symptoms. Sleep disturbances are not only a diagnostic criterion of depression but also function as an independent risk factor for its onset, persistence, and recurrence (Baglioni et al., 2011; Riemann et al., 2020). Importantly, accumulating evidence supports a bidirectional relationship between sleep problems and depression, suggesting that impaired sleep may exacerbate emotional dysregulation and negative affect, which in turn further deteriorate sleep quality (Goldstein & Walker, 2014).

Given these converging lines of evidence, recent research has increasingly examined the interrelationships among social media addiction, sleep quality, and depression. While many studies report that excessive social media use is associated with poorer sleep quality and higher depressive symptoms, findings across studies remain heterogeneous with respect to effect sizes, sample characteristics, cultural contexts, and age groups. Moreover, most existing studies rely on cross-sectional designs and bivariate analyses, limiting their ability to clarify indirect pathways or test integrative theoretical models that simultaneously account for these relationships.

Critically, despite the proliferation of meta-analyses examining pairwise associations (e.g., SMA–sleep, sleep–depression, SMA–depression), no prior study has systematically synthesized these relationships within a unified causal framework using Meta-Analytic Structural Equation Modeling (MASEM). This represents a significant gap in the literature, as MASEM allows for the simultaneous estimation of direct and indirect effects based on pooled evidence, thereby providing a more rigorous test of theoretical models than traditional meta-analytic approaches.

Addressing this gap, the present study employs a two-stage MASEM approach to examine whether sleep quality functions as a mediating mechanism linking social media addiction to depressive symptoms. By integrating evidence from multiple quantitative studies across diverse populations, this study aims to (1) quantify the direct associations among social media addiction, sleep quality, and depression; (2) test the indirect pathway through which social media addiction influences depression via sleep quality; and (3) explore potential moderators such as age and cultural context. In doing so, this research provides novel insights into the mechanisms underlying digital media–related mental health risks and highlights sleep quality as a critical intervention target in efforts to mitigate the psychological consequences of excessive social media use.

2. Review of Literature

2.1 Significance of Sleep Quality

Sleep quality reflects an individual's energy, functioning, and sense of restoration upon waking, and serves as a vital indicator of physical and mental well-being (Ancoli-Israel et al., 1991). It is a combination of both qualitative and quantitative measures, such as sleep duration, sleep-onset latency, the sleep intensity, depth, and sense of restfulness upon awakening (Buysse et al., 1989), necessary for maintaining mood, memory, and cognitive performance, and general psychological well-being. Poor quality of sleep may lead to worsened physical and psychiatric issues, raise the risk of occupational or automobile accidents, decrease performance or impairment while daytime education or job, as a result decreased quality of life of an individual (Mollayeva et al., 2016). Additionally, poor sleep was found to be a predictor of poor cognitive performance in healthy elderly community residing in the United States (Nebes et al., 2009). Regularly having trouble falling asleep has been linked to greater mortality in males but not in women (Lallukka et al., 2015). Plethora of studies have indicated that inadequate sleep quality is a significant predictor of suicidal thoughts and depressive symptoms among the elderly population (Gelaye et al., 2016; Livingston et al., 1990; Sukegawa et al., 2003). Further the amount of sleep reported at night is a strong predictor of mortality as both insufficient and excessive sleep are linked to an increased risk of death (Burazeri et al., 2003; Kripke, 1979; Youngstedt & Kripke, 2004).

2.2 Effect of Social Media Addiction (SMA) on Sleep Quality (SQ)

In the present scenario, developments in the tech world and changes in the preferences of young people and families concerning electronic devices have boosted children's and their parents' screen time (Rodriguez & Merryman, 2021). In a situation where smartphones are overly used, a person may become miserable and/or anxious and, as a consequence, may have trouble sleeping (Demirci et al., 2015). Overuse of social media can contribute to misuse, dependency, and addiction(Griffiths, 2012). It has been reported that as smartphones have become more popular and advanced in technological features, many teenagers have developed the habit of using them before going to sleep, which has the ability to delay sleep onset and reduce sleep time (Yang et al., 2019). Among the factors affect the sleep quality of college students is internet usage as the use of smartphones may bring about poor sleep quality while depressive and anxious symptoms may also increase (Demirci et al., 2015). The results of PSQI reveal that the group of students with moderate to severe internet addiction, specifically Snapchat and Twitter had significantly worse sleep quality than the group of students with minimal or no internet addiction (Lin et al., 2019; Nowell & Thompson, 2020). Similarly, the use of technology at night has a negative impact on the sleep of university students and may cause hypersomnia(Nasirudeen et al., 2017). Further, it was found that the psychological impact of smartphone use was substantially more for female adolescents than for male ones (Yang et al., 2019). Moreover, the previous research has also shown that the use of such electronic media as TV, video games, and the internet may deteriorate the quality of one's sleep (Choi et al., 2009). In the same vein, it was revealed that the people who were labeled as dependent on SNS were 1.3 times more likely to experience poor sleep quality than those without SNS dependence symptoms (Wolniczak et al., 2013). Besides, the excessive use of social media has been related to worsened sleep quality and increased occurrence of cognitive errors during the daytime (Xanidis & Brignell, 2016).

The excessive use of mobile phones, texting, instant messaging, emailing, and other digital communication manners has been the cause of sleep deprivation among adolescents (Moore & Meltzer, 2008).The reason for this lies in the fact that blue light is emitted by display units and this light interferes with the body's inherent circadian rhythm and has an adverse effect on sleep (Barion & Zee, 2007). Internet addiction may result in social isolation, as students may prefer virtual communication to face-to-face interaction. As a result, this gradual drifting apart can weaken the bond of real friendships, which is one of the major factors that have been strongly associated with the onset of depressive symptoms (Tonioni et al., 2012).

2.3 Effect of Sleep Quality (SQ) on Depression (DPS)

Poor sleep quality can arise from numerous factors, including physical health conditions, medication side effects, chronic illnesses, and neurodegenerative disorders, and is also commonly associated with mental health conditions such as depression, anxiety, and schizophrenia (Livingston et al., 2017; Ohayon et al., 2017). Additionally, poor sleep is associated with an increased frequency as well as the severity of symptoms related to depression, anxiety, and stress (Pensuksan et al., 2016). University students from all over the world are to a great extent suffering from bad sleep quality (Jiang et al., 2015, internet addiction(Yang et al., 2013), and depressive symptoms (Ibrahim et al., 2013).Roughly 5% of adult people worldwide are estimated to suffer from depression at some point in their lives (Moreno-Agostino et al., 2021; Remes et al., 2021). Nearly 90% of people with depression report that they have poor sleep quality, and almost 40% of major depressive disorder patients have insomnia-related symptoms, such as difficulty in falling asleep, staying asleep, and waking up too early (Tsuno et al., 2005). Despite the problems caused by depressive disorders and their severity, treatment rates are still quite low, and hence, fewer than 10% of those affected get proper and effective care. Especially in China, the problem of lack of proper indication and treatment of depression is very serious (Li et al., 2021).

Sleep is extremely important for different psychological mechanisms, among which cognitive functioning is one (Joo et al., 2021). To a great extent, as a matter of fact, one of the fundamental depression diagnostic criteria is the change in sleep habits. Almost 70% of people with depression undergo sleep disorders, which may vary from insomnia, oversleeping, nightmares, and even changes in the sleep-wake cycle (Yan et al., 2021). Research findings reveal the existence of a two-way relationship i.e. with insomnia being not only a symptom but also a risk factor of depression (Riemann, 2003). Besides the negative impact on mood, lack of sleep is known to be harmful to the cardiovascular, endocrine, and immune systems as well (Choi et al., 2018; Kim et al., 2019; Spiegel et al., 1999). Furthermore, sleep disturbances can elevate levels of the stress hormone cortisol, potentially leading to inflammation in the brain and tissue damage (Born & Fehm, 2000). Moreover, extremely short or long sleep durations are strongly linked to increased mortality risk (Grandner et al., 2010).

2.4 The Proposed Model of the Study

Building on the framework discussed (section 2.2 and 2.3), in the current study, four hypotheses are tested via meta-analytic structural equation modeling (MASEM) approach: (H1) Social Media Addiction (SMA) is positively related to poor Sleep Quality (SQ); (H2) Low Sleep Quality (SQ) is positively related to Depression (DPS); (H3) Social Media Addiction (SMA) positively associated with Depression (DPS); and (H4) SQ moderates the association between SMA and DPS. A schematic model of the study presented in Figure 1.

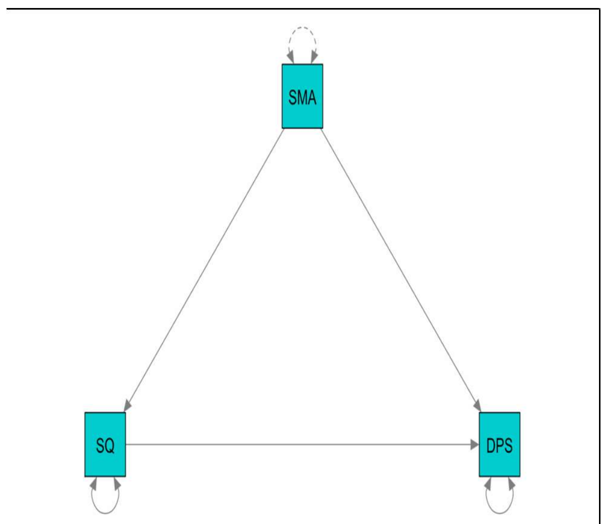


Figure 1. Proposed model of the Study

Methodology

3.1 Research Design and Data Collection

A systematic literature search was conducted, considering studies correlating sleep quality, depression, and social media addiction. A comprehensive literature search was done in the Scopus database with the query TITLE-ABS-KEY (("Sleep Quality") AND ("Social Media Addiction" OR "Screen Time" OR "Facebook Use" OR "YouTube Use" OR "Internet Use") AND ("Depression")) that resulted in a pool of records identified initially totaling 207 articles (Figure 2). After screening the titles and abstracts, 57 records were removed since they were out of the scope of the review, leaving 150 articles for a full-text eligibility evaluation. 118 articles were excluded after the detailed full-text examination for the following reasons: 89 were non-frequent research of sleep quality, social media use/addiction, and depression (the core relationship between the three variables), 20 used qualitative methodologies, 5 had no relevant or extractable data, and 4 full-text articles were inaccessible. Consequently, 32 studies fulfilled the complete criteria of inclusion and were further used for the qualitative and quantitative meta-analysis.

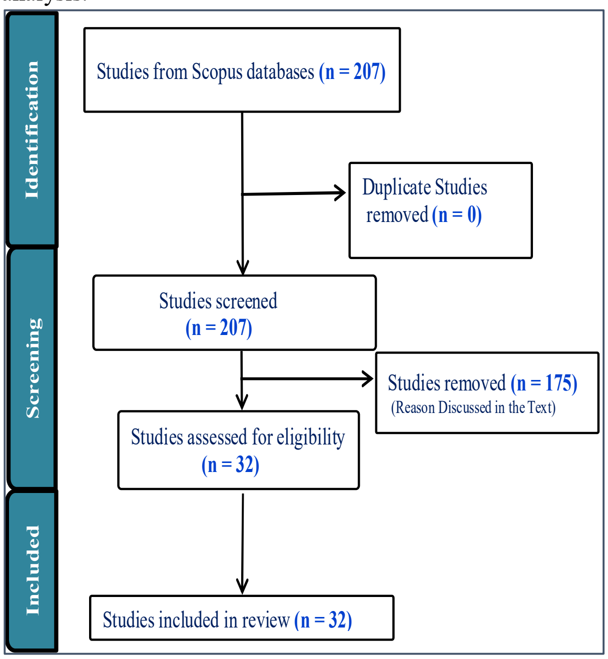


Figure 2. PRISMA Flow Diagram

3.2 Data Analysis

3.2.1 Calculation of Overall Effect Sizes

Before testing the mediation model, bivariate associations between depression (DPS), social media addiction (SMA), and sleep quality (SQ) were synthesized. Overall effect sizes (Pearson's Correlation) were computed. To allow normality for analysis, these correlations were converted to Fisher's Z scores and then back to Pearson's Correlation for interpretation, as per the standard procedure for meta-analysing correlation coefficients (Borenstein et al., 2021).

A random-effects model was used for all initial meta-analytic estimates, on the premise that the studies included were sampled from populations with differing true effect sizes (Borenstein et al., 2021; Hedges & Vevea, 1998). For sensitivity analysis, a common-effect (fixed-effect) model was also calculated, and the consistency of results between the two models attested to the stability of the pooled estimates.

The sizes of the effect were interpreted based on the benchmarks outlined by Lovakov and Agadullina (Lovakov & Agadullina, 2021) for social psychology studies, where $r = 0.12, 0.24$, and 0.41 represent small, medium, and large effects, respectively.

3.2.2 Evaluation of Heterogeneity and Moderator Analysis

Heterogeneity among the effect sizes included was measured using the I^2 statistic, which represents the percentage of total variation across studies due to true heterogeneity as opposed to chance. The I^2 values of 25%, 50%, and 75% represent low, moderate, and high heterogeneity, respectively. (Higgins, 2003)The Q-statistic was also utilized to test the significance of the heterogeneity ($p < 0.05$).

To investigate sources of heterogeneity, moderators (Country, Age, Gender) analyses were conducted. Moreover, a meta-regression analysis was used to investigate the impact of mentioned moderators.

3.2.3 Publication Bias Diagnostics

A range of procedures was used to evaluate possible publication bias. Contour-enhanced funnel plots were visually examined, overlaying significance areas (e.g., $p <$ 0.10, 0.05, 0.01) to distinguish asymmetry resulting from bias and other causes (Peters et al., 2008). Egger's regression test (Egger et al., 1997) and Begg's rank correlation test(Begg & Mazumdar, 1994) were applied statistically to test for funnel plot asymmetry. Furthermore, the trim-and-fill procedure (Duval & Tweedie, 2000a, 2000b) was used to impute missing studies and calculate adjusted overall effect sizes.

3.2.4 Testing the Mediation Model

The hypothesized mediation model, where social media addiction (SMA) mediates the DPS-SQ relationship, was tested employing meta-analytic structural equation modeling (MASEM). The two-stage structural equation modeling (TSSEM) approach was used (Cheung & Chan, 2005; Jak & Cheung, 2020). For Stage 1, a pooled correlation matrix was estimated for all studies entered under the random-effects model. For Stage 2, this matrix was employed to estimate the mediation model through weighted least squares estimation.

All analyses were conducted within the R statistical software. The meta-analysis was run with the meta package,(Schwarzer, 2007) and the MASEM analyses with the metaSEM package (Cheung, 2015).

Results

A series of random-effects meta-analyses were performed to combine evidence on the three central construct relationships: SMA–SQ, DPS–SQ, and SMA–DPS. Each effect size was taken from primary studies and weighted by its inverse variance. The combined findings were consistent with all three relationships being positive and statistically significant (Table 1), in support of the hypothesized relationships. The Construct-wise detail meta-analysis were discussed in subsequent sections.

Table 1. Overall Effect Size and Heterogeneity

Relations	k	Effect Size	Fail-safe N	S.E.	95% CI Lower Limit	95% CI Upper Limit	Z value	p value	τ^2	I^2	H^2
DPS--SQ	29	0.259	28174	0.085	0.093	0.426	3.056	2.24E-03**	0.208	99.663	297.435
SMA--DPS	32	0.325	50311	0.029	0.269	0.381	11.342	8.08E-30***	0.025	97.179	35.453
SMA--SQ	32	0.237	25357	0.045	0.148	0.327	5.22	1.78E-07***	0.065	98.899	90.826

Overall Effect Size between SMA and SQ

The overall effect size of the relationship between SMA and SQ was determined by the correlation coefficients across 32 studies obtained from 45667 participants. Figure 3 displays the forest plot of the effect sizes.

The aggregated effect size was 0.237, representing a small-to-moderate positive relation, significant at the 0.001 level ($Z = 5.220$, $p < 0.001$). The 95% confidence interval (0.148–0.327) also validated the significance of the relation. The fail-safe N was 25,357, emphasizing that it is not easy to attribute the result to publication bias. However, there are considerable heterogeneity ($Q = 90.826$, $I^2 = 98.899\%$, $\tau^2 = 0.065$), indicating study variability that demands further moderator examination. Hence, A mixed-effects meta-regression was performed on the same sample to test the effects of age, country, and gender on the observed effect sizes presented in (Table 2)

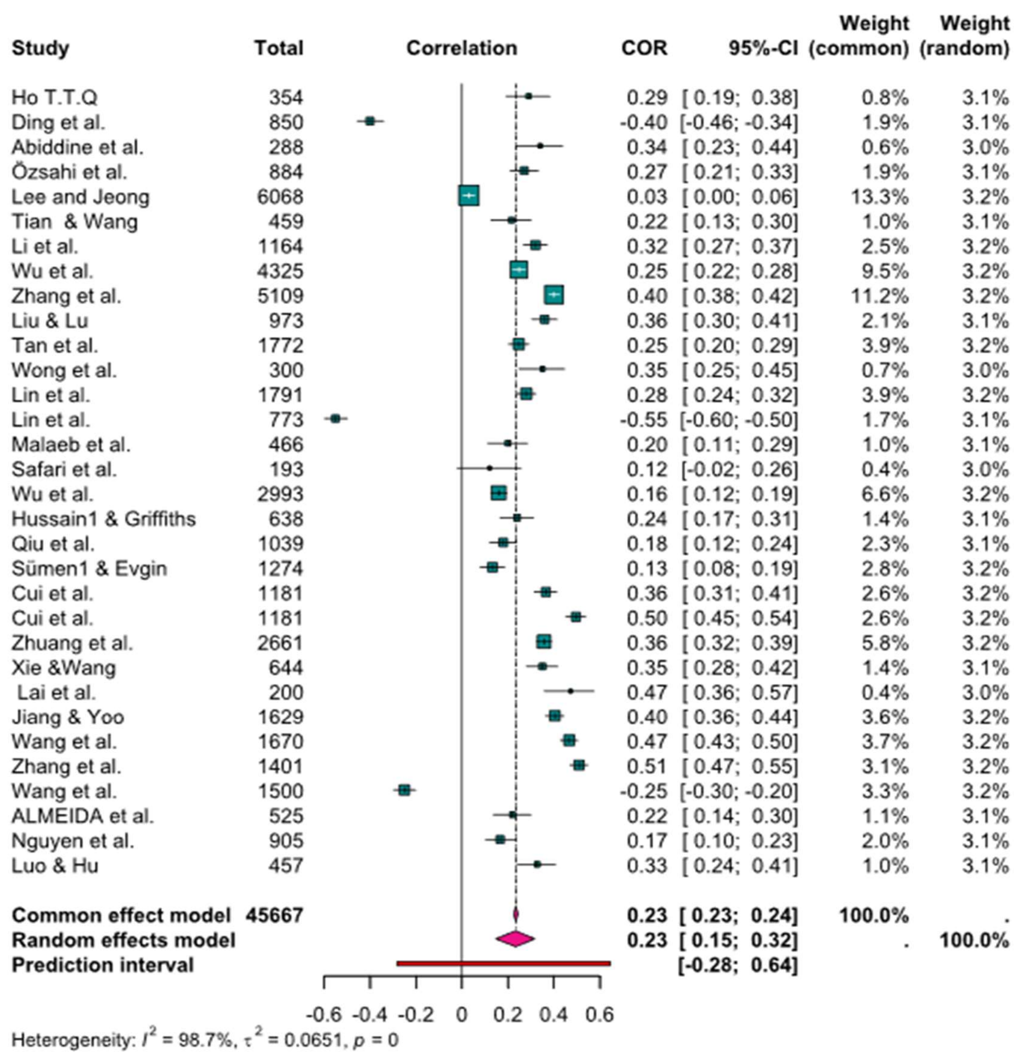


Figure 3. Forest Plot of Correlation between SMA and SQ

Even after including these moderators, the model revealed significant and substantial residual heterogeneity ($\tau^2 = 0.0504$, SE = 0.0172; $I^2 = 98.64\%$), indicating that a high proportion of variance in effect sizes is still unexplained by the given predictors. The moderators collectively explained a moderate low percentage of the overall variance ($R^2 = 22.54\%$).

Table 2. Meta regression (SMA-SQ)

Moderator	Estimate	S.E.	Z value	p value	95% CI (Lower- Upper)	Significance
Intercept	0.4150	0.2445	1.70	0.090	[-0.064, 0.894]	NS
Age	-0.0029	0.0037	-0.79	0.427	[-0.010, 0.004]	NS
China	-0.2643	0.2582	-1.02	0.306	[-0.770, 0.242]	NS
Global	-0.3453	0.3497	-0.99	0.323	[-1.031, 0.340]	NS
Iran	-0.0478	0.3247	-0.15	0.883	[-0.684, 0.589]	NS
Italy	-1.2660	0.3525	-3.59	0.0003	[-1.957, -0.575]	***
Korea	-0.5854	0.3472	-1.69	0.092	[-1.266, 0.095]	NS
Lebanon	-0.1325	0.3271	-0.40	0.686	[-0.774, 0.509]	NS
Portugal	-0.1259	0.3260	-0.39	0.699	[-0.765, 0.513]	NS
Taiwan	-0.4422	0.3585	-1.23	0.217	[-1.145, 0.261]	NS
Turkey	-0.1571	0.2823	-0.56	0.578	[-0.710, 0.396]	NS
Vietnam	-0.1895	0.3247	-0.58	0.560	[-0.826, 0.447]	NS
Gender: Male	0.2687	0.1280	2.10	0.036	[0.018, 0.520]	*

Note: Significance at: ***p<.001 **p<.01; *p<.05, **NS**-Non-Significant
Model Fit Statistics: τ^2=0.0504 (SE=0.0172), I^2=98.64%, H^2=73.59, R^2=22.54%, Test for residual heterogeneity: QE (18) =1013.78, p<.0001, Test of moderators: QM (13) =21.68, p=0.0605

The omnibus test of all moderators was borderline non-significant (QM (13) = 21.68, p = .061), which suggests that the collection of predictors did not quite achieve conventional statistical significance in collectively explaining heterogeneity. Nevertheless, a test of residual heterogeneity established that the unexplained variance remaining was significant (QE (18) = 1013.78, p < .0001), highlighting the presence of some additional, unexplored sources of variation.
Individual moderator coefficients were examined, and two considerable effects were found. The Italian studies had a significantly smaller pooled effect size than the reference category (β = −1.27, SE = 0.35, z = −3.59, p = .0003, 95% CI [−1.96, −0.58]). In contrast, a greater percentage of male participants in the study samples was related to a large significant effect size increase (β = 0.27, SE = 0.13, z = 2.10, p = .036, 95% CI [0.02, 0.52]). The intercept, i.e., the estimated effect size for the reference group, was positive but not significant (β = 0.42, SE = 0.24, p = .090). No other age- or country-level moderator showed statistically significant associations, and the Korean coefficient came close to significance (p = .092).

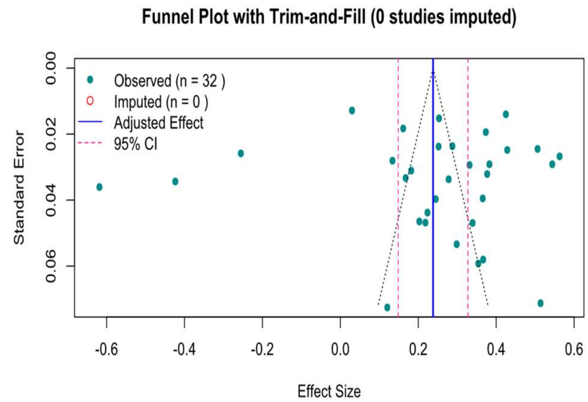


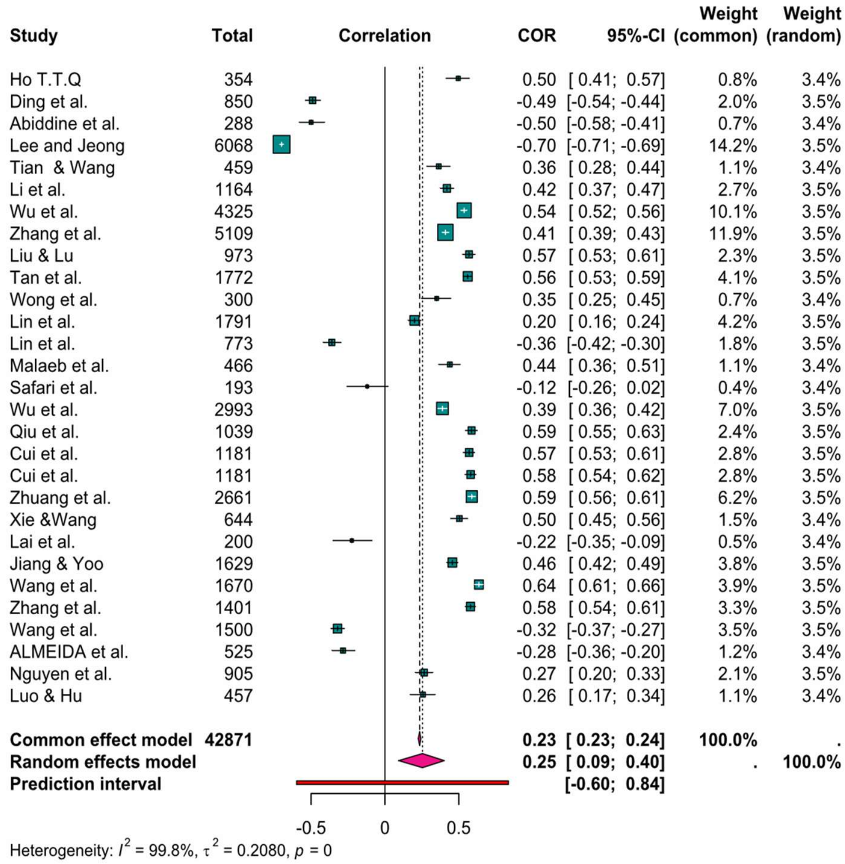
Figure 4. Contour funnel plot of the correlation between SMA and SQ

Examining the contour-enhanced funnel plot (Figure 4) to asses for possible chance of publication bias on the overall effect size. Although the distribution of studies was not perfectly symmetrical (z = -0.79; p = 0.4268), according to Begg and Mazumdar's rank correlation test, there seemed to be no evidence for substantial publication bias with a bias estimate of -49.0000 (SE = 61.6577). The linear regression test (t = −0.02, df = 30, p = 0.9855) of Egger was also non-significant with an estimate for a bias of −0.0697 (SE: 3.7969). The expected overall effect size was estimated as r = 0.237 (95% CI [0.148, 0.327]), which is also in accord with the initial pooled effect of r = 0.23. Trim-and-fill analysis yielded no imputed studies, providing additional evidence that publication bias did not substantially influence the meta-analytic results.

Overall Effect Size between DPS and SQ

A meta-analysis of 29 independent studies, which included 42,871 observations, was used to estimate the pooled correlation coefficient (Figure 5). The common effect model was calculated using Fisher's z transformation of correlations and the inverse variance method with a pooled correlation of 0.2349 (95% CI: 0.2259–0.2439, z = 49.52, p < 0.001). The random-effects model, which was estimated using restricted maximum likelihood, resulted in a pooled correlation of 0.2541 (95% CI: 0.0929–0.4023, z = 3.06, p = 0.002). The 95% prediction interval was extremely broad (−0.5984 to 0.8367), which means that subsequent studies might have very unpredictable results, varying from a negative to a strong positive correlation.
Heterogeneity analysis indicated significant between-study variation. The estimated between-study variance was τ^2 = 0.2080 (95% CI: 0.1304–0.3815). The inconsistency index was very high (I^2 = 99.8%), and the heterogeneity statistic was statistically significant (Q (28) = 12,494.51, p < 0.001), reinforcing significant heterogeneity among studies.

Figure 5. Forest Plot of Correlation between DPS and SQ



A mixed-effects meta-regression was conducted (Table 3) to examine whether age, country, and participant gender moderate the strength of association between depression and sleep quality that is observed. The analysis indicated that the factors as a group accounted for a large proportion of between-study variance such that moderators explained 50.67% of the heterogeneity. The omnibus test also validated the set of moderators as statistically significant (QM (11) = 39.35, p < .0001).

Despite this explanatory ability, there was still significant residual heterogeneity (τ^2 = 0.1026, SE = 0.0356; I^2 = 99.34%), and the test for residual heterogeneity was significant (QE (17) = 1938.90, p < .0001), which means that other, unmeasured factors contribute to the depression-sleep quality correlation.

Table 3. Meta-Regression (DPS-SQ)

Moderator	Estimate	S.E.	Z value	p value	95% CI (Lower - Upper)	Significance
Intercept	-0.2800	0.3433	-0.82	0.415	[-0.953, 0.393]	NS
Age	-0.0129	0.0052	-2.49	0.013	[-0.023, -0.003]	*
China	0.8238	0.3633	2.27	0.023	[0.112, 1.536]	*
Iran	0.8344	0.4587	1.82	0.069	[-0.065, 1.733]	NS
Italy	-0.1652	0.4978	-0.33	0.740	[-1.141, 0.810]	NS
Korea	-0.5131	0.4914	-1.04	0.296	[-1.476, 0.450]	NS
Lebanon	1.1051	0.4605	2.40	0.016	[0.203, 2.008]	*
Portugal	0.2774	0.4591	0.60	0.546	[-0.622, 1.177]	NS
Taiwan	0.4661	0.5022	0.93	0.353	[-0.518, 1.450]	NS
Vietnam	0.8089	0.4581	1.77	0.077	[-0.089, 1.707]	NS
Gender: Male	0.2278	0.1821	1.25	0.211	[-0.129, 0.585]	NS

Note: Significance at: ***p<.001 **p<.01; *p<.05, **NS**- Non-Significant

Model Fit Statistics: τ^2=0.1026 (SE=0.0356), I^2=99.34%, H^2=151.23, R^2=50.67%, Test for residual heterogeneity: QE (17) =1938.90, p<.0001, Test of moderators: QM (11) =39.35, p<.0001

As per the moderators are concerned, age showed a strong negative correlation with the effect size (β = -0.0129, SE = 0.0052, p = .013), which suggests that the positive correlation between poor sleep quality and depression declines as sample age increases. Again, country-level analyses uncovered significant geographical moderation. In comparison with the reference country, research conducted in China (β = 0.824, p = .023) and Lebanon (β = 1.105, p = .016) found a significantly larger depression-sleep quality correlation. The effects for Iran (p = .069), and Vietnam (p = .077) were close to, but did not achieve, statistical significance. The prevalence of male participants in the samples and model intercept were not significant predictors.

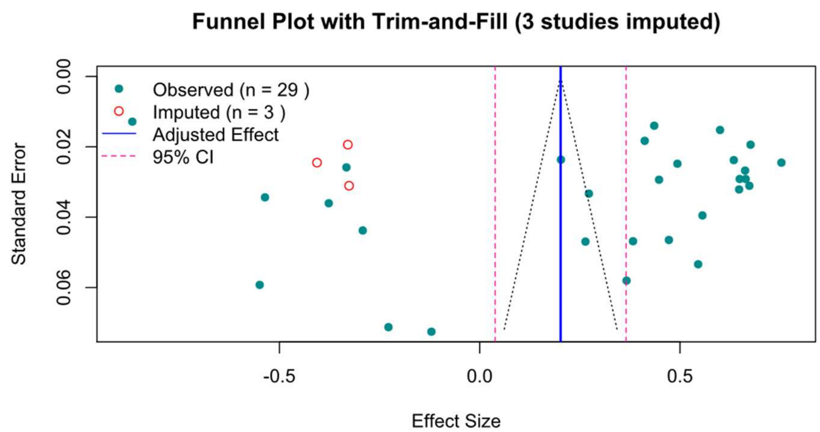


Figure 6. Contour funnel plot of the correlation between DPS and SQ

A funnel plot (Figure 6), as enhanced by a contour-enhanced funnel plot was examined for publication bias in the overall effect size. Although all studies were included in the 95% confidence interval, the effect size distribution was skewed, with a number of studies falling outside funnel boundaries. However, there was no evidence of significant publication bias according to Egger's regression test (p = 0.481) and pointing to the non-significant asymmetry that was observed in the funnel plot. To investigate this issue, a trim-and-fill analysis was carried out, imputing three additional studies and yielding an adjusted overall effect estimate of 0.202 (95% CI [0.038, 0.365]). The original pooled effect was at medium level (r = 0.25), but the bias-corrected estimate moved down from medium to a low level (r = 0.20), which in turn suggests that publication bias may have been existent.

Overall Effect Size between SMA and DPS

A meta-analysis (Figure 7) of 32 studies (N = 45,667) with Fisher's z transformation revealed a pooled correlation of 0.32 (95% CI: 0.31–0.33, z = 70.25, p < 0.001) under the common-effect model. The random-effects model provided an equivalent estimate of 0.31 (95% CI: 0.26–0.36, z = 11.34, p < 0.001). The 95% prediction interval (−0.002 to 0.57) indicated that any future study could vary from essentially no association to a moderately strong positive relationship. Between-study heterogeneity was considerable (τ^2 = 0.025, I^2 = 96.4%, Q (31) = 857.09, p < 0.001), which meant that a large majority of the observed variation represented true differences between studies, not sampling variability.

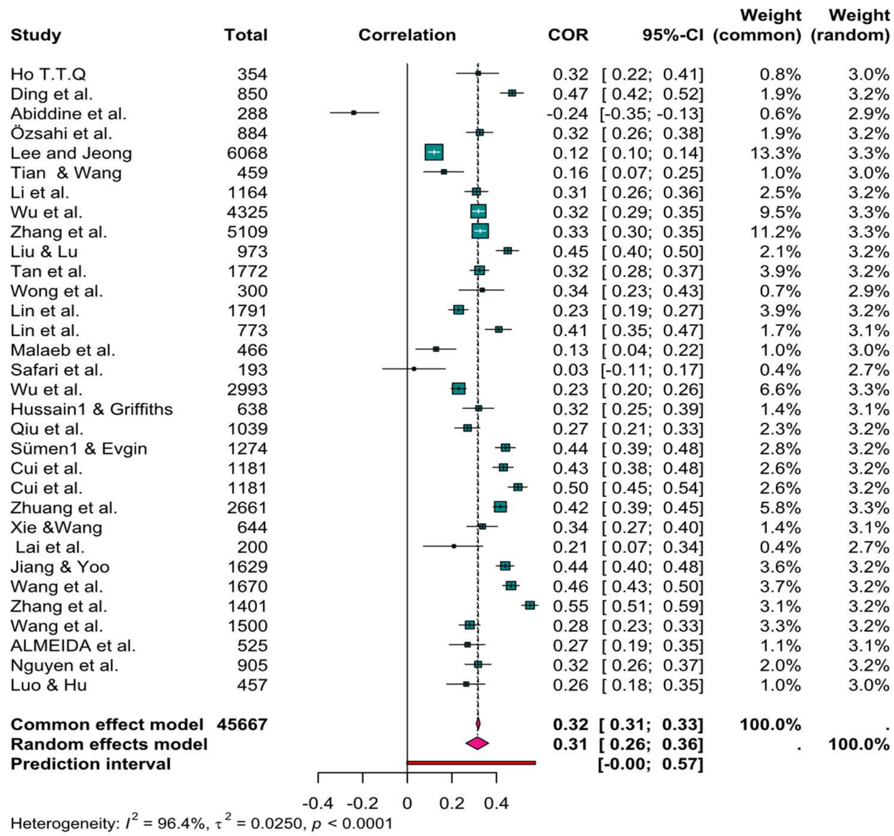


Figure 7. Forest Plot of Correlation between SMA and DPS

A meta-regression of 32 mixed studies was conducted (Table 4) to investigate the impact of study variables on the relation (effect size, r) between depression and social media addiction. The model indicated considerable unexplained heterogeneity (τ^2=0.0102, SE=0.0037), with high residual heterogeneity (I^2=93.62%; H^2=15.67). Nevertheless, the moderators explained 59.17% of the observed heterogeneity (R^2=59.17%). The residual heterogeneity test was still significant (QE (18) =289.53, p<.0001), and the omnibus moderator test verified that study characteristics accounted for significant variation in effect sizes (QM (13) =52.58, p<.0001).

Table 4. Meta-Regression (SMA-DPS)

Moderator	Estimate	S.E.	Z value	p value	95% CI (Lower - Upper)	Significance
Intercept	-0.140	0.123	-1.13	0.257	[-0.381, 0.102]	**NS**
Age	-0.005	0.002	-2.78	0.006	[-0.009, -0.002]	**
China	0.616	0.128	4.81	<.0001	[0.365, 0.867]	***
Global	0.605	0.170	3.55	0.0004	[0.271, 0.939]	***
Iran	0.511	0.157	3.26	0.001	[0.204, 0.818]	**
Italy	0.610	0.171	3.57	0.0004	[0.275, 0.944]	***
Korea	0.350	0.166	2.11	0.035	[0.025, 0.675]	*
Lebanon	0.407	0.162	2.52	0.012	[0.090, 0.724]	*
Portugal	0.530	0.161	3.30	0.001	[0.215, 0.844]	***
Taiwan	0.351	0.183	1.92	0.055	[-0.007, 0.708]	**NS**
Turkey	0.636	0.139	4.57	<.0001	[0.363, 0.908]	***
Vietnam	0.568	0.158	3.59	0.0003	[0.258, 0.878]	***
Gender: Male	0.028	0.059	0.47	0.636	[-0.088, 0.143]	**NS**

Note: Significance at: ***p<.001 **p<.01; *p<.05, **NS**- Non-Significant

Model Fit Statistics: τ^2=0.0102(SE=0.0037), I^2=93.62%, H^2=15.67, R^2=59.17%. Residual Heterogeneity: QE (18) =289.5, p<.0001. Test of moderators: QM (13) =52.58, p<.0001

Among predictors, age was significantly and negatively related to effect size (β=−0.005, SE=0.002, z=−2.78, p=0.006), indicating lower correlations between social media addiction and depression in older samples. For all of the countries, the relationship was significantly stronger than the reference group, including China (β=0.616, SE=0.128, p<.0001), Global samples (β=0.605, SE=0.170, p=0.0004), Iran (β=0.511, SE=0.157, p=0.001), Italy (β=0.610, SE=0.171, p=0.0004), Korea (β=0.350, SE=0.166, p=0.035), Lebanon (β=0.407, SE=0.162, p=0.012), Portugal (β=0.530, SE=0.161, p=0.001), Turkey (β=0.636, SE=0.139, p<.0001), and Vietnam (β=0.568, SE=0.158, p=0.0003). In comparison, Taiwan's effect only approached significance (p=0.055). Moreover, gender moderator (male) was also not a substantial predictor (β=0.028, SE=0.059, p=0.636).

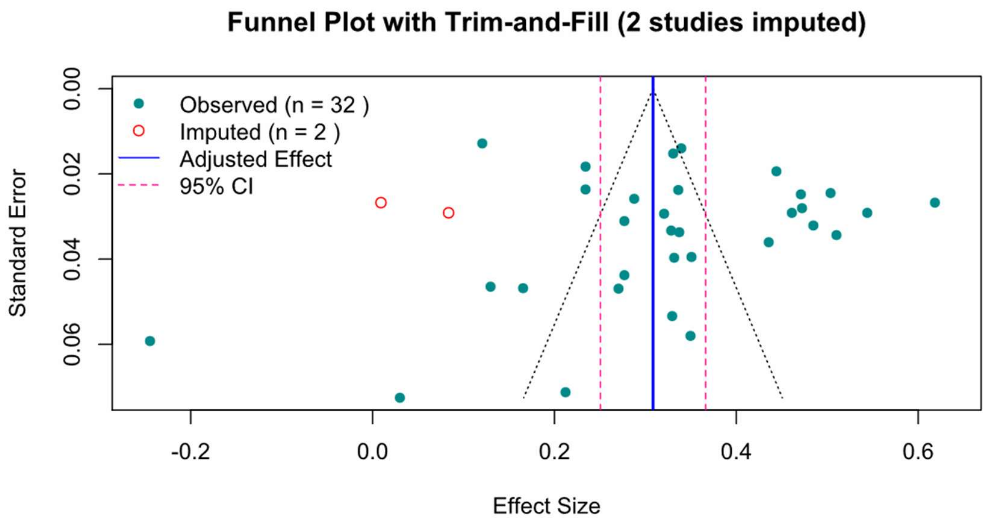


Figure 8. Contour funnel plot of the correlation between SMA and DPS

The contour-enhanced funnel plot (Figure 8) was examined to evaluate the potential presence of publication bias in the overall effect size. Egger's linear regression test of funnel plot asymmetry showed no appreciable evidence of publication bias (t (30) = 0.59, p = 0.562; bias estimate = 1.33, SE = 2.27). In the same manner, Begg and Mazumdar's rank correlation test also failed to detect statistically significant asymmetry (z = −1.74, p = 0.083; bias estimate = −107.00, SE = 61.66). Since the funnel plot was perfectly symmetrical, a trim-and-fill analysis was performed to calculate an unbiases effect size. This analysis imputed 2 studies and produced an adjusted overall effect of r = 0.308 (95% CI: 0.250–0.366), which is also in accord with the initial pooled effect of r = 0.31. These findings indicate that publication bias is not likely to have substantially affected the reported meta-analytic results.

Pathways Associating Social Media Addiction, Sleep Quality, and Depression

To examine the association of SQ on the relationship between SMA and DPS, correlation matrices were constructed using correlation coefficients derived from 30 studies (Two studies removed to maintain large sample size). The heterogeneity test indicated significant variability across the matrices (χ^2 = 142.20, p < 0.001) with high I^2 values. Consequently, in the first stage of MASEM, the correlation matrices were synthesized using a random-effects model. In the second stage, the pooled correlation matrix obtained from Stage 1 was employed to evaluate the fit of the proposed structural model. The path diagram of the proposed mediation model presented in Figure 9.

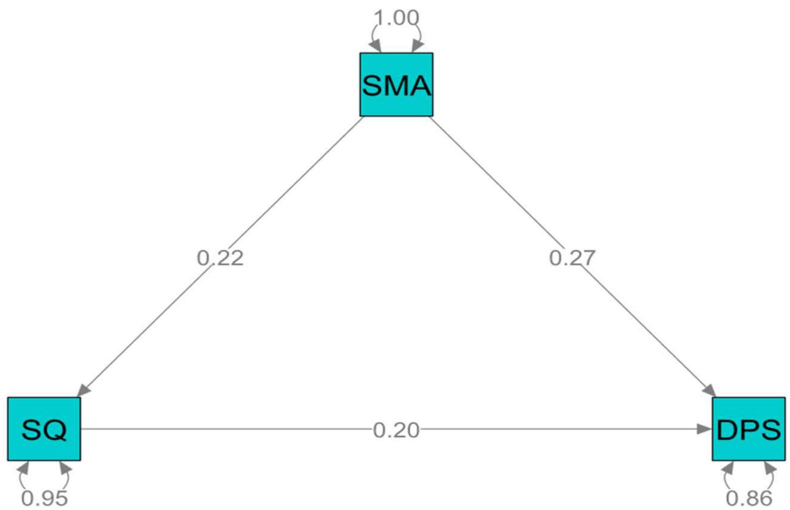


Figure 9. MASEM results for the proposed model

The meta-analytic structural equation model (Table 5) identified a strong pathway where social media addiction (SMA) significantly predicted poor quality of sleep (SQ; β = 0.224, 95% CI [0.139, 0.309], p< .001). This is in agreement with previous literature that has shown that prolonged usage of social media, especially at night, interferes with sleep in various ways such as exposure to blue light, psychological activation, and delayed onset of sleep (Cain & Gradisar, 2010; Exelmans & Van den Bulck, 2016; Scott & Woods, 2018).

Conversely, low sleep quality strongly predicts depressive symptoms (β = 0.202, 95% CI [0.043, 0.362], p = .012), lending evidence to sleep quality as an associative pathway in social media addiction-depression. This is in line with longitudinal studies showing that sleep disturbances are both antecedents to and outcomes of depressive disorders (Alvaro et al., 2013; Baglioni et al., 2011).

The indirect effect of SMA on depression via SQ implies partial mediation, which means that social media addiction affects depressive symptoms both directly and indirectly through sleep disturbance. This intricate relationship warrants theoretical frameworks hypothesizing that digital media consumption impacts mental health through various avenues, such as substituting restorative activities and interfering with circadian rhythms (Kardefelt-Winther, 2014).

The direct relation between SMA and depression (β = 0.274, 95% CI [0.209, 0.339], p < .001) was also significant after controlling for the mediating role of sleep quality, indicating other mechanisms aside from sleep disturbance might be accounting for this relationship, such as social comparison processes, fear of missing out (FoMO), or decreased face-to-face social interaction (Primack et al., 2017; Valkenburg et al., 2006).

Table 5. Result of SEM path analysis

Relations	Estimate	Std. Error	95% CI (Lower–Upper)	z-value	p-value	Interpretation
DPS→SMA	0.274	0.0331	0.209-0.339	8.266	2.22e-16 ***	**Accepted**
DPS→SQ	0.202	0.081	0.043-0.362	2.499	0.01245 *	**Accepted**
SQ→SMA	0.224	0.043	0.139-0.309	5.191	2.09e-07 ***	**Accepted**

Discussion

This meta-analytic research presents a quantitative integration of the complicated interrelations among social media addiction (SMA), sleep quality (SQ), and depression (DPS). The findings reflect strong, positive correlations between all three variables in favor of the proposed model. The largest correlation was found between DPS and SMA (r = 0.325), highlighting the direct connection between excessive social media usage and increased depressive symptoms, as held by theories of social comparison and fear of missing out (Primack et al., 2017; Valkenburg et al., 2006). In addition, the results showed that poor quality sleep was strongly correlated with increased social media addiction (r = 0.237) and depression (r = 0.254), as reported in literature on the undesirable consequences of screen exposure on sleep and the mutual interaction between sleep disorders and mood disorders(Baglioni et al., 2011, 2016; Cain & Gradisar, 2010).

The main strength of the research is the tested structural model. Through the application of meta-analytic structural equation modeling (MASEM), it was established that sleep quality has strong association with social media addiction-depression pathway. This suggests that the negative effect of SMA on mental health works through two channels: a direct channel and an indirect channel where heavy social media use undermines sleep quality, which subsequently increases depressive symptoms. This outcome aligns with biopsychosocial theories, which posit that the use of technology may adversely affect mental health by, for instance, lessening sleep quality, a vital physiological mechanism, and thus reducing psychological resilience(Kardefelt-Winther, 2014; Twenge & Park, 2019). Importantly, the analyses revealed significant variations between the studies included in the meta-analysis, and a considerable part of this variation was explained by the variables moderating effects such as age and country. The size of the relationships, particularly between SMA and DPS and between DPS and SQ, was smaller in older samples, which suggested that there were developmental or cohort-specific risks. The differences in the effects in different parts of the world, with the most substantial effects observed in countries like China and Lebanon, indicate that cultural contexts might moderate these associations and are thus helpful for the next cross-cultural studies to be conducted in this field.

By establishing sleep quality as an associating factor, it theoretically extends existing models of technology use and mental health. It supports the findings of previous research that sleep quality significantly mediates the connection between technology or social media use and depression and anxiety symptoms in the adolescent and young adult population (Alonzo et al., 2021; Levenson et al., 2016). Scott & Woods, 2018, showed that sleep quality and duration are among the mediators through which social media usage may impact adolescents' mental health outcomes. Similarly, Marino et al., 2018, established very firm associations between the adverse use of social media, disturbances in sleep, and the deterioration of psychological health in the case of children. The results suggest that sleep hygiene-related interventions, such as limited exposure to screens in bed or at night or encouraging a habit of going to bed and waking up at the same time daily, can reduce the negative effects of SMA on mental health.

Plethora of studies explored through sleep-hygiene interventions targeting the adolescent population have yielded positive outcomes, for instances, a randomized pilot trial was successful in both changing adolescents' sleep habits and reducing their daytime sleepiness and depressive symptoms (Beattie et al., 2015); a cluster randomized controlled trial demonstrated that a theory-driven program on sleep hygiene led to better sleep health (Moseley & Gradisar, 2009); and group interventions carried out in schools resulted in lasting improvements in sleep routines (Allen et al., 2013). Additionally, behavioral interventions targeted at sleep disorders in children have also been shown to increase knowledge about sleep, self-efficacy, and the willingness to adopt healthy habits (Blake et al., 2017). Consequently, poor sleep quality and excessive social media use have been concurrently identified as risk factors for depression and other mental health conditions (Levenson et al., 2016).The claim of this causal pathway is substantiated by longitudinal studies showing that increases in social media use during early adolescence leads to increased depressive symptoms with time (Boers et al., 2019), which is also consistent with the systematic reviews reporting that sleep disturbances constitute a major pathway through which excessive social media use results in poor mental health in young people (Alonzo et al., 2021). The above-highlighted evidence sets out the necessity of efforts for sensitization and screening aimed at detecting unhealthy social media behaviors, particularly in the young people and youths, as well as the importance of the development of suitable and effective prevention strategies and policies.

Limitations

The high heterogeneity, even after moderator testing, indicates the possibility that other unmeasured factors, including varying assessment measures or sample demographics, could affect the relationships. The majority of cross-sectional studies included in the meta-analysis rule out definitive causal conclusions; longitudinal work is needed to establish directionality of the mediation pathway. Additionally, the geographical concentration of studies in Asian contexts, particularly China, raises concerns about the generalizability of results to Western populations with different digital and cultural environments, indicating a need for more diverse cultural representation in future research. Finally, although publication bias tests revealed minimal distortion, the exclusion of gray literature and non-significant findings cannot be ruled out.

Conclusion

This study presents full evidence of the relationship between social media addiction and sleep quality and the occurrence of depression using a meta-analytic structural equation modeling (MASEM) methodology. The results indicate that there is a strong association between social media addiction and poor sleep quality as well as high levels of depressive symptoms and sleep quality partially mediates the relationship. These findings indicate that overuse of social media has not only direct but also indirect psychological effects, but also increases the susceptibility to depression by interfering with sleeping habits.

Theoretical implications support the need to adopt the integrative frameworks to explain the behavioral, physiological, and psychological processes in the context of learning about the digital-mental health nexus. In practical terms the research demonstrates the significance of interventions aimed at digital well-being and sleep hygiene especially within the adolescent age group and young adults. Diagnostic checks on sleeping disorders can also serve as a predictor of depression among the high social media users.

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Data Availability Statement: All data generated or analyzed in this study are presented within the article.

Additional details may be obtained from the corresponding author upon request

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