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Original Article

The Interplay of Sleep Disturbance, Fear of Missing Out and Emotional Reactivity to Social Media Use in Adolescence

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Abstract

Objective: This study aims to transcend the limitations of aggregate screen time metrics by investigating the granular affective dynamics and emotional reactivity associated with specific social media behaviors in adolescents, while also incorporating the constructs of sleep quality and fear of missing out (FoMO).
Method: A cohort of 346 adolescents participated in a 21-day ecological momentary assessment (EMA) protocol, receiving five prompts daily. Participants reported real-time social media activities (passive scrolling versus active interaction), concurrent affect, and pre-sleep social media use. Baseline and follow-up depressive symptoms were assessed using the patient health questionnaire-9 (PHQ-9). Additional measures included the FoMO scale and the Pittsburgh sleep quality index (PSQI). We utilized dynamic structural equation modeling (DSEM) to analyze within-person temporal associations and machine learning (random forest) to identify behavioral predictors of depression.
Results: For 328 adolescents who completed the EMA protocol, DSEM revealed that passive scrolling predicted subsequent increases in negative affect ($\beta = 0.31$, $P < 0.001$), whereas active interaction predicted increased positive affect ($\beta = 0.22$, $P = 0.003$). High FoMO significantly moderated the relationship between passive use and negative affect ($\beta = 0.15$, $P = 0.01$). Furthermore, two distinct mediation pathways were identified. First, nighttime social media use mediated the association between daily passive scrolling and poorer next-day sleep quality (indirect effect = -0.10, 95% CI [-0.15, -0.05]). Second, aggregated poor sleep quality over the study period mediated the relationship between average passive scrolling and increased depressive symptoms at follow-up (indirect effect = 0.12, 95% CI [0.05, 0.19]). The machine learning model achieved high predictive accuracy for PHQ-9 scores ($R^2 = 0.76$, RMSE = 2.31), identifying high-frequency passive use, elevated FoMO, and delayed sleep onset as primary risk factors.
Conclusion: The findings demonstrate that the emotional impact of social media is contingent upon usage patterns and individual traits like FoMO. Passive consumption was prospectively associated with negative emotional spirals and disrupted sleep, highlighting the need for interventions targeting specific digital behaviors and evening routines rather than total screen time.

Key words: *Anxiety; Adolescence; Emotion; Social Media; Sleep*

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The rapid proliferation of social media has fundamentally reshaped the landscape of adolescent development, creating a digital environment where social interaction, identity formation, and emotional regulation increasingly occur online (1). As digital natives, today's adolescents spend a significant portion of their waking hours engaged on platforms such as Instagram, TikTok, and Snapchat (2). This unprecedented level of connectivity has sparked intense debate within the scientific community regarding its implications for youth mental health. While correlational studies have frequently linked high overall screen time to increased rates of internalizing disorders, particularly depression and anxiety, the findings remain inconsistent (3, 4). A growing body of evidence suggests that the relationship is not merely a function of duration; rather, it is the complex interplay of how adolescents use these platforms, why they use them, and how they react emotionally that determines psychological outcomes (5, 6).

Traditional research methodologies have largely relied on retrospective, self-report surveys that aggregate social media use into global metrics, such as daily hours spent online (7, 8). While useful for broad epidemiological trends, these measures lack the granularity to capture the dynamic, moment-to-moment fluctuations in affect and behavior that characterize the digital experience. Adolescence is a period marked by heightened emotional reactivity and increased sensitivity to social evaluation (9). Consequently, the impact of social media is likely instantaneous and transactional, a nuance that is lost in cross-sectional designs. To address this limitation, researchers have turned to ecological momentary assessment (EMA), a methodological approach that captures data in real-time within naturalistic settings (10). EMA allows for the examination of within-person processes, enabling researchers to determine if a specific episode of social media use leads to an immediate shift in mood, and vice versa (11).

Despite these methodological advancements, significant gaps persist in the literature. First, existing EMA studies often treat social media use as a monolithic construct (12). However, the psychological impact of passively scrolling through idealized content is likely distinct from the impact of actively messaging friends or posting content. Theoretical frameworks, such as the social displacement hypothesis and the social comparison theory, suggest that passive consumption may trigger maladaptive upward comparisons leading to negative affect (NA), whereas active interaction may provide social support and enhance positive affect (PA, 13, 14). Disentangling these behavioral modalities is essential for understanding the specific mechanisms driving mental health outcomes. Moreover, individual differences in susceptibility to social media influences are often overlooked. The construct of fear of missing out (FoMO) (i.e., the pervasive apprehension that others might be having rewarding experiences from which one is absent) has emerged as a critical moderator (15, 16). Adolescents with high FoMO may engage in compulsive checking behaviors not for enjoyment, but to alleviate anxiety, potentially creating a feedback loop of NA and increased usage (17). Furthermore, the intersection of social media use and sleep hygiene represents a critical yet underexplored pathway to depression (18, 19). The displacement hypothesis of sleep suggests that late-night social media use displaces essential sleep time (20), while the arousal hypothesis posits that the psychological and physiological stimulation from blue light and emotional content delays sleep onset (21). Poor sleep quality is a robust predictor of depressive symptomatology (22). Thus, investigating the mediating role of sleep in the link between social media behaviors and mood is a vital area of inquiry.

Finally, while the identification of risk factors is crucial, there is a pressing need for studies that leverage advanced computational techniques to predict clinical outcomes. Traditional statistical models, while interpretable, are often limited in their ability to handle the high-dimensional, nonlinear data generated by intensive EMA protocols (23). Machine learning approaches offer a novel avenue for identifying complex patterns of behavior that serve as early warning signs for depression. By integrating granular EMA data with trait measures like FoMO and objective sleep parameters, researchers can develop more accurate predictive models. Therefore, the present study aims to bridge these gaps by employing a 21-day intensive longitudinal design to examine the affective dynamics of social media use in adolescents. We move beyond aggregate screen time to differentiate between passive and active usage behaviors. Furthermore, we investigate the moderating roles of FoMO and sleep quality in the relationship between social media engagement and depressive symptoms. By combining dynamic structural equation modeling (DSEM) with machine learning algorithms, this study seeks to provide a comprehensive, nuanced understanding of the digital determinants of adolescent mental health, paving the way for targeted, just-in-time interventions. We propose an integrated conceptual framework linking social media behaviors to adolescent depressive symptoms through two primary pathways. First, a direct affective pathway posits that passive scrolling triggers upward social comparisons, leading to increased NA, whereas active interaction fosters social connection and enhances PA. This pathway is moderated by individual differences in FoMO, such that adolescents high in FoMO exhibit a stronger negative affective response to passive consumption. Second, an indirect sleep-mediated pathway posits that passive scrolling, particularly in the evening, disrupts sleep through both displacement (replacing sleep time) and arousal (physiological and cognitive stimulation) mechanisms, and that this sleep disruption, in turn, contributes to depressive symptoms.

Together, these pathways suggest that the emotional impact of social media is not uniform but depends on usage modality, individual susceptibility, and sleep hygiene.

Materials and Methods

Participants

A total of 346 adolescents (aged 13-18 years) were recruited from secondary schools and youth community centers between February 2025 and May 2025 using a convenience sampling approach. Recruitment strategies involved a multi-pronged approach, including the distribution of digital flyers through school mailing lists, announcements in school assemblies, and physical posters displayed in community youth centers. Inclusion criteria required participants to own a smartphone compatible with the study application and to be active social media users (defined as at least 30 minutes of daily usage). Exclusion criteria included a current diagnosis of a severe psychiatric disorder (e.g., psychosis, bipolar disorder) or a diagnosed sleep disorder (e.g., sleep apnea, narcolepsy) that could independently account for mood disturbances or sleep disruptions. These conditions were screened using a preliminary online health questionnaire and a brief structured interview. The study protocol was approved by the relevant Institutional Review Board (IRB). Written informed assent was obtained from the adolescent participants, and written informed consent was obtained from their parents or legal guardians.

The sample size of 346 participants was determined based on a priori power considerations for the primary analyses. For the DSEM and multilevel mediation models, power analyses were guided by simulation studies showing that a sample of 100-150 participants with 5 daily assessments over 21 days provides sufficient power (≥0.80) to detect small-to-medium within-person effects in intensive longitudinal designs (24). Given the complexity of the cross-level interactions and the moderated mediation model, we conservatively targeted 350 participants to provide a buffer against attrition and missing data. This sample size is consistent with recent EMA studies examining similar research questions (11, 25), and exceeds the minimum of 200 participants recommended for stable estimation of random forest regression models with up to 20 predictors (26). With our final sample of 328 participants (retaining those with >70% compliance), power for detecting a small-to-medium effect ($\beta = 0.15$) at $\alpha = 0.05$ is estimated at >0.85 for the DSEM analyses and >0.80 for the random forest model based on prior simulation benchmarks (27).

Study procedure

This study employed a 21-day intensive longitudinal design utilizing EMA to capture the dynamic interplay between social media behaviors, affective states, and sleep patterns in adolescents. Participants were instructed to download a custom-designed mobile application secured for research purposes. The EMA phase spanned 21 consecutive days. To balance data density with participant compliance, the application delivered five semi-random prompts per day within a fixed 14-hour window (e.g., 09:00 to 23:00). The semi-random schedule ensured that prompts were distributed evenly across waking hours, with a minimum interval of 90 minutes between alerts to prevent fatigue. Upon receiving a prompt, participants had a 20-minute window to respond. If a response was not logged within this timeframe, the prompt was marked as missed. Additionally, participants completed a dedicated bedtime survey within 30 minutes before self-reported sleep onset and a morning survey immediately upon waking to capture sleep-related variables.

Measures

There were two types of measurements in this study. First, participants were subjected to baseline (day 0) and follow-up (day 22) assessments for depressive symptoms, FoMO, and sleep quality. Moreover, at baseline, participants reported their age, gender, grade level, and household socioeconomic status (parental education and income). They also provided information regarding their primary social media platforms and general smartphone usage habits to control for potential confounding variables in the analysis. Second, the EMA procedure was designed to capture high-resolution data on participants' digital behaviors, affective states, and sleep patterns in their natural environments. All EMA measures were administered via a custom mobile application.

Patient Health Questionnaire-9 (PHQ-9). This 9-item self-report instrument is widely used in clinical and research settings to assess the frequency of depressive symptoms over the preceding two-week period. Items correspond to the Diagnostic and Statistical Manual of Mental Disorders IV (DSM-IV) criteria for major depressive disorder (e.g., little interest or pleasure in doing things and feeling down, depressed, or hopeless). Each item is scored on a 4-point scale from 0 (Not at all) to 3 (Nearly every day). Total scores range from 0 to 27, with higher scores indicating greater severity. The PHQ-9 was administered at baseline (day 0) and at the end of the 21-day EMA period (day 22) to evaluate changes in symptomatology. The Uzbek version of this scale has been previously validated and used (28). In the current study, Cronbach's α for the PHQ-9 total score was 0.85. We did not apply a clinical cutoff, and instead, we used the continuous total score as a measure of depressive symptom severity.

Fear of Missing Out Scale (FoMOs). The tendency to experience anxiety over missing out on rewarding experiences experienced by others was assessed using the 10-item FoMOs. Participants rated statements such as "I get anxious when I don't know what my friends are up to" on a 5-point Likert scale ranging from 1 (Not at all true of me) to 5 (Extremely true of me). The total score is computed by summing all item responses, with possible scores ranging from 10 to 50. Higher scores indicate a greater dispositional FoMO. This measure was administered at baseline to serve as a trait-level moderator variable. The Uzbek version of this scale has been previously validated and used (29). In the current study, Cronbach's α for the FoMOs total score was 0.89.

Pittsburgh Sleep Quality Index (PSQI). The PSQI is a 19-item self-report questionnaire that evaluates sleep quality over the previous month. It generates seven component scores: subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. These components are summed to yield a global score ranging from 0 to 21, with a score greater than 5 indicative of poor sleep quality. This measure provided a trait-level baseline against which the EMA-derived sleep data were compared. The Uzbek version of this scale has been previously validated and used (30). In the current study, Cronbach's α for the PSQI global score was 0.81. It is important to note that the PSQI assesses global sleep quality over the previous month, whereas the EMA component of the study collected daily sleep data over the subsequent 21 days. Thus, while the PSQI provided a trait-level baseline measure of habitual sleep quality, it should not be treated as equivalent to the daily EMA-derived sleep outcomes (sleep duration, sleep onset latency, and subjective sleep quality reported each morning), which capture state-level fluctuations during the study period.

EMA application variables. To address the lack of granularity in previous research, social media engagement was assessed through multi-dimensional items rather than a simple duration metric. At each prompt, participants were asked to report their social media activity since the last signal. First, they estimated the total duration of use in minutes. Subsequently, they were presented with a checklist to categorize the nature of their usage into three distinct behavioral modalities: passive scrolling (defined as browsing news feeds, viewing stories, or watching videos without direct interaction), active interaction (defined as direct engagement with others, including sending private messages, commenting on posts, or participating in group chats), and content broadcasting (defined as creating and posting original content, such as uploading photos, videos, or status updates). Participants could select multiple categories if applicable. This approach allowed for the calculation of both the duration and the proportional composition of different social media behaviors. Moreover, current affect was measured using a modified version of the positive and negative affect schedule (PANAS), adapted for EMA protocols. Participants were asked to rate the extent to which they experienced specific emotions at that moment on a 5-point Likert scale ranging from 1 (Very slightly or not at all) to 5 (Extremely). This included the NA subscale which consisted of afraid, nervous, sad, upset, and hostile items as well as the PA subscale which consisted of excited, enthusiastic, proud, happy, and active items. Composite scores for NA and PA were calculated by averaging the respective items at each assessment point. Higher scores indicated greater intensity of that affective dimension. Short versions of the PANAS have shown strong within-person reliability in adolescent samples (31). In the current study, we assessed the multilevel reliability of the modified PANAS using generalizability theory, separating within-person (moment-to-moment) and between-person (individual differences) variance. Cronbach's α values at the between-person level were 0.89 (PA) and 0.87 (NA). Within-person reliability (i.e., the reliability of within-person fluctuations across time) was assessed using the procedure described by Cranford *et al.* (32), yielding reliability of change values of 0.78 (PA) and 0.75 (NA), indicating adequate reliability for detecting within-person changes in affect across the 21-day protocol.

In addition, to capture the intersection of social media use and sleep hygiene, two specialized EMA reports were utilized. (I) Bedtime report: Triggered within a 30-minute window before the participant's self-reported intended sleep time, this survey asked, "Did you use social media in the 30 minutes before trying to sleep?" (Yes/No). If yes, participants indicated the primary modality (Passive vs. Active). (II) Morning report: Triggered immediately upon waking, this survey collected data on the previous night's sleep duration (in hours and minutes) and sleep onset latency (time taken to fall asleep). Participants also rated their sleep quality on a single-item visual analogue scale from 0 (Terrible) to 10 (Excellent).

Statistical analysis

EMA data were first screened for compliance. Participants with a response rate of less than 70% were excluded. The final analytic dataset was structured hierarchically, with prompts (Level 1) nested within days (Level 2), nested within individuals (Level 3). We utilized DSEM to examine the within-person temporal associations between social media use and affect. This multilevel modeling approach allowed us to test concurrent and lagged effects (e.g., whether passive scrolling predicted subsequent NA) while accounting for the autocorrelation inherent in intensive longitudinal data. DSEM examined within-person associations between social media use and affect using Mplus (version 8.10). Level 1 predictors were person-mean centered. Random intercepts and slopes were specified at individual level. Bayesian estimation with Gibbs sampling handled missing data. Model fit was assessed using posterior predictive P-value and deviance information criterion (DIC), with potential scale reduction (PSR) factor < 1.05 indicating convergence. To account for pre-existing depressive symptoms, baseline PHQ-9 scores were included as a covariate in all mediation models. To establish temporal ordering in the mediation analyses, we leveraged the temporal structure of the EMA data. For the first mediation pathway (passive scrolling → nighttime use → sleep quality), temporal ordering was established as follows: (I) daily passive scrolling (X) was assessed across each day; (II) nighttime use (M) was assessed within 30 minutes prior to self-reported bedtime on the same day; and (III) sleep quality (Y) was assessed the following morning. This sequential ordering ensures that X precedes M, and M precedes Y in time. For the second mediation pathway (average passive scrolling → poor sleep → PHQ-9 at follow-up), the temporal ordering was: (I) average passive scrolling aggregated over the 21-day period (X), (II) aggregated poor sleep quality over the 21-day period (M), and (III) PHQ-9 measured at day 22 (Y). This design ensures that X and M are measured before Y.

We also tested cross-level interactions to determine if trait FoMO moderated these within-person associations. Multilevel mediation models were used to test whether nighttime social media use mediated the relationship between daily passive scrolling and sleep quality/depressive symptoms. In addition, to predict the severity of depressive symptoms (continuous PHQ-9 scores at follow-up), we employed a supervised machine learning algorithm: random forest regression. Given the number of hypotheses tested across multiple outcomes and analytical approaches, we implemented a hierarchical strategy to control Type I error. For the primary DSEM analyses (six models testing the within-person effects of social media behaviors on affect), we applied Benjamini-Hochberg false discovery rate (FDR) correction with a q-value threshold of 0.05 to account for multiple testing across the six models. For the cross-level interaction tests (FoMO moderation), mediation analyses (two indirect effects), and random forest regression, we treated these as separate analytic families and applied FDR correction within each family. Before applying the prediction model, feature engineering was performed, including aggregating EMA data into summary statistics (e.g., mean proportion of passive use, variability in NA and PA, frequency of nighttime use, etc.). The dataset was split into training (80%) and testing (20%) sets (33, 34). Model performance was evaluated using the root mean square error (RMSE) and the coefficient of determination (R2). To ensure unbiased evaluation of predictive performance, all data-dependent preprocessing and feature engineering steps were performed exclusively within the training data, with the test data held completely separate until final evaluation. Feature importance analysis was conducted to identify the strongest predictors of depression using the mean decrease in impurity (MDI) method provided by the random forest algorithm (35). This metric quantifies the total reduction in the Gini impurity criterion achieved by splits on each variable, averaged across all trees in the ensemble. All analyses were performed using R (version 4.3.1) and Mplus for DSEM, with Python (scikit-learn) used for machine learning components. The significance level was set at $P < 0.05$.

Results

After excluding 18 participants with EMA compliance rates below 70%, the final analytic sample consisted of 328 adolescents (mean age = 15.7 ± 1.4 years, 58% female). Participants provided an average of 89.2 ± 12.4 EMA responses over the 21-day protocol, resulting in an overall compliance rate of 84.9%. At baseline, the mean PHQ-9 score was 7.2 ± 4.8 (range 0-23), the mean FoMO score was 28.4 ± 9.1 (range 10-48), and the mean PSQI global score was 6.1 ± 3.2, indicating overall poor sleep quality in the sample. Participants were distributed across six schools (n = 218, 66.5%) and three youth centers (n = 110, 33.5%). Intra-class correlation coefficients (ICC) for the primary outcomes (PHQ-9, sleep quality, NA) ranged from 0.02 to 0.07, indicating that between-site variability accounted for only a small proportion of the total variance in the outcomes. Table 1 summarizes the key sample characteristics and baseline measures.

Table 1. Sociodemographic Characteristics, Baseline Psychological Measures, and Social Media Use Characteristics of Adolescents Participating in the Study (N = 328)

Variable	Mean (SD) or %	Range
Age (years)	15.7 (1.4)	13-18
Gender (% female)	58%	
Baseline PHQ-9	7.2 (4.8)	0-23
Baseline FoMO	28.4 (9.1)	10-48
Baseline PSQI	6.1 (3.2)	1-18
EMA compliance rate	84.9% (8.7%)	70-100%
Average daily social media use (mins)	142.5 (61.3)	35-310
Proportion of passive use	0.62 (0.18)	0.15-0.95

DSEM revealed significant within-person temporal associations between specific social media behaviors and subsequent affect, accounting for the nested structure of the data (prompts within days within individuals), while controlling for autocorrelation of affective states. As shown in Table 2, passive scrolling predicted a significant increase in NA at the subsequent assessment point ($\beta = 0.31$, 95% CI [0.24, 0.38], $P < 0.001$), and a modest decrease in PA ($\beta = -0.09$, 95% CI [-0.17, -0.01], $P = 0.03$). In contrast, active interaction predicted increased PA ($\beta = 0.22$, 95% CI [0.08, 0.36], $P = 0.003$) but showed no significant association with NA ($\beta = -0.04$, $P = 0.41$). Content broadcasting demonstrated no significant lagged effects on either affective dimension ($|\beta| < 0.06$, $P > 0.10$).

Table 2. Within-Person Lagged Associations Between Specific Social Media Behaviors and Subsequent Positive and Negative Affect Among Adolescents (N = 328)

Predictor	Outcome	β	95% CI	P-value
Passive scrolling	Negative affect (t+1)	0.31	[0.24, 0.38]	< 0.001
Passive scrolling	Positive affect (t+1)	-0.09	[-0.17, -0.01]	0.03
Active interaction	Positive affect (t+1)	0.22	[0.08, 0.36]	0.003
Active interaction	Negative affect (t+1)	-0.04	[-0.14, 0.06]	0.41
Content broadcasting	Positive affect (t+1)	0.05	[-0.03, 0.13]	0.22
Content broadcasting	Negative affect (t+1)	-0.02	[-0.10, 0.06]	0.62

Note: t+1 = next assessment point. Models control for autocorrelation of affect. β = standardized coefficient.

The moderating role of trait-level FoMO was significant. A cross-level interaction indicated that adolescents with higher baseline FoMO scores exhibited a stronger positive association between passive scrolling and subsequent NA (βinteraction = 0.15, 95% CI [0.04, 0.26], P = 0.01). Simple slope analysis (Figure 1) revealed that the within-person effect of passive use on NA was pronounced for individuals with high FoMO (+1 SD: β = 0.42, P < 0.001), but attenuated for those with low FoMO (-1 SD: β = 0.20, P = 0.02).

Multilevel mediation models tested the pathway from daily social media behavior to sleep outcomes and depressive symptoms, controlling for baseline PHQ-9 scores and using bias-corrected bootstrap confidence intervals (5,000 resamples). As presented in Table 3, the proportion of daily time spent in passive scrolling was positively associated with a higher likelihood of nighttime social media use (i.e., use within 30 minutes before self-reported bedtime; β = 0.35, P < 0.001). In turn, nighttime use, particularly passive use before bed, was associated with poorer subjective sleep quality reported the next morning (β = -0.28, 95% CI [-0.39, -0.17], P < 0.001) and longer sleep onset latency (β = 0.24, 95% CI [0.13, 0.35], P < 0.001). In addition, a significant indirect effect was found so that greater daily passive scrolling predicted poorer next-day sleep quality through increased nighttime use (ab = -0.10, 95% CI [-0.15, -0.05]). Furthermore, aggregated poorer sleep quality over the study period mediated the relationship between higher average passive scrolling and increased PHQ-9 scores at follow-up (ab = 0.12, 95% CI [0.05, 0.19]). All mediation effects remained significant after adjusting for baseline PHQ-9.

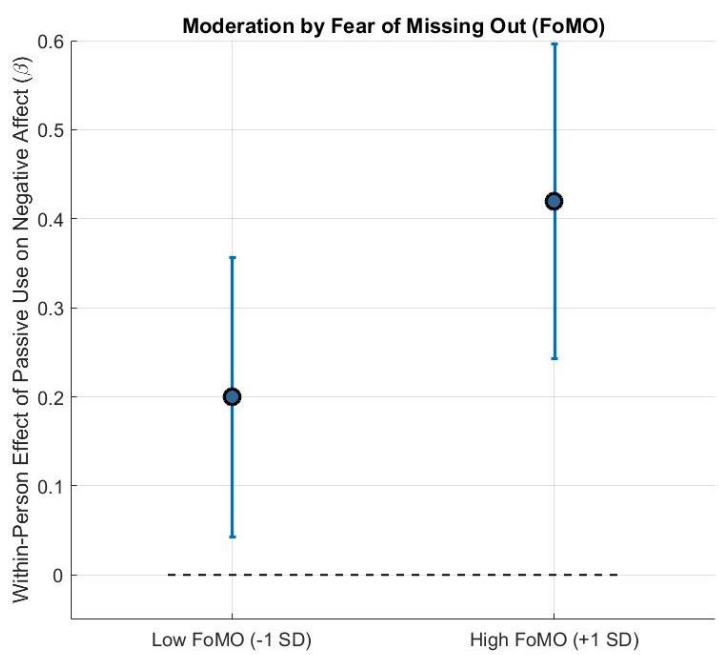

Figure 1. Simple Slopes Illustrating the Moderating Effect of Baseline Fear of Missing Out (FoMO) on the Within-Person Association Between Passive Social Media Scrolling and Subsequent Negative Affect Among Adolescents (N = 328)

Table 3. Multilevel Mediation Pathways: Passive Scrolling, Nighttime Use, Sleep, and Depression in the Adolescent Sample

Path / Effect	β / ab	95% CI	P-value
Path a: Passive scrolling → Nighttime use	0.35	[0.27, 0.43]	< 0.001
Path b1: Nighttime use → Sleep quality (next day)	-0.28	[-0.39, -0.17]	< 0.001
Path b2: Nighttime use → Sleep onset latency	0.24	[0.13, 0.35]	< 0.001
Indirect Effect 1: Passive → Nighttime → Sleep quality	-0.10	[-0.15, -0.05]	< 0.001
Indirect Effect 2: Passive → Poor sleep → PHQ-9 (Follow-up)	0.12	[0.05, 0.19]	0.001

Note: β = standardized coefficient for direct paths; ab = standardized indirect effect. Nighttime use = social media use within 30 minutes before bedtime.

A random forest regression model was trained to predict follow-up PHQ-9 scores (as a continuous variable) using aggregated EMA features, baseline scores (FoMO, PSQI), and demographic variables. The model demonstrated high predictive accuracy on the held-out test set (20% of data), achieving an R^2 of 0.76 and an RMSE of 2.31. Feature importance analysis, based on the MDI, identified the top ten predictors. The primary risk factors, in descending order of importance, were baseline PHQ-9 score, mean proportion of daily passive scrolling, baseline FoMO score, mean sleep onset latency (from morning reports), variability (SD) of NA, frequency of nighttime social media use, baseline PSQI global score, mean PA, gender, and variability (SD) of PA. Figure 2 shows the plots related to both feature importance analysis and the model's predictive performance (observed vs. predicted values).

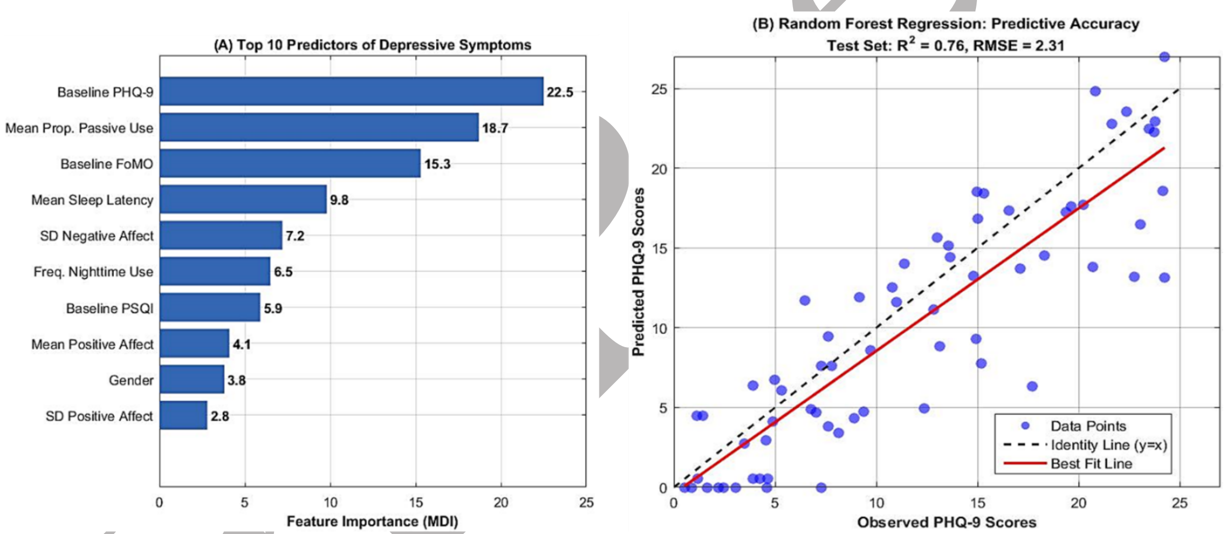

Figure 2. Random Forest Regression Model Performance for Predicting Depressive Symptoms Among Adolescents Based on Social Media Use and Related Behavioral Measures (N = 328)

(A) Relative importance of behavioral, psychological, and sleep-related predictors. (B) Scatter plot illustrating the model's predictive accuracy (R^2 = 0.76) for observed versus predicted PHQ-9 scores in the test set.

Discussion

The present study utilized an intensive longitudinal design to disentangle the complex affective dynamics linking social media use to adolescent mental health. By integrating DSEM with machine learning (random forest regression), we moved beyond aggregate screen time metrics to reveal that the nature of usage and individual traits are critical determinants of emotional outcomes. Our findings highlight a distinct divergence between passive consumption and active interaction, underscore the exacerbating role of FoMO, and establish sleep disruption as a key physiological pathway linking digital habits to depressive symptoms. These associations are consistent with a causal pathway but should be interpreted with caution given the observational nature of the data. Consistent with social comparison theory (36), our DSEM results demonstrated that passive scrolling was prospectively associated with subsequent increases in NA. The temporal sequence revealed here (i.e., passive use predicting subsequent increases in NA) is consistent with the notion that browsing idealized content may trigger maladaptive upward comparisons. Conversely, active interaction predicted subsequent increases in PA, aligning with the social capital hypothesis, which posits that direct messaging and commenting enhance feelings of connection and support. Consistent with our findings, Thorisdottir *et al.* (37) showed that passive social media use was associated with greater symptoms of anxiety and depressed mood among adolescents, while active use was linked to fewer symptoms. Moreover, a recent meta-analysis reported that passive use is associated with worse emotional outcomes in general contexts, and active use is associated with greater online support (38). This dichotomy suggests that interventions focusing solely on reducing screen time may be misguided; rather, the quality of digital engagement should be targeted. Encouraging adolescents to shift from passive consumption to active, connection-oriented behaviors could serve as a protective factor against negative emotional spirals.

A significant contribution of this study is the identification of FoMO as a critical moderator. The amplified NA response to passive scrolling among high-FoMO adolescents suggests a vulnerability loop (39). For these individuals, social media is not merely a leisure activity, but an anxiety-driven ritual. The compulsive checking behavior inherent in high FoMO likely prevents the emotional detachment necessary to process the idealized images encountered during passive scrolling, thereby deepening NA (40). This finding emphasizes that “one size fits all” guidelines are insufficient. Rather, adolescents with high dispositional FoMO may require specific cognitive-behavioral strategies to manage the anxiety associated with digital connectivity. Furthermore, this study elucidates the physiological mechanisms through which social media exerts its longitudinal influence on depression. Our mediation analysis confirmed that nighttime social media use serves as a bridge between daily passive habits and poor sleep quality, which is consistent with existing evidence (41-43). The displacement and arousal hypotheses are both supported here: passive scrolling likely displaces sleep time, while the cognitive and physiological arousal induced by blue light and emotional content delays sleep onset (44, 45). Given that poor sleep quality mediated the pathway to higher PHQ-9 scores, these findings suggest that sleep hygiene is a modifiable target for mitigating the depressive risk associated with social media. Interventions enforcing digital curfews may be particularly effective for the subset of adolescents who engage in high-frequency passive scrolling. It should be noted that the use of both PSQI (trait-level baseline) and EMA-derived daily sleep measures (state-level) allowed us to examine sleep at two distinct levels. The mediation analyses relied on EMA-derived sleep measures, which capture the immediate consequences of nighttime social media use, while the PSQI provided a baseline indicator of habitual sleep quality. This distinction is important because nightly fluctuations in sleep may be more proximally related to daily social media behaviors than global sleep quality assessed over the past month.

The application of random forest regression provided a robust, data-driven confirmation of these clinical insights. The model achieved high predictive accuracy (R2 = 0.76), identifying the mean proportion of passive scrolling, baseline FoMO, and sleep onset latency as top predictors of depressive symptom severity. Notably, the feature importance analysis ranked baseline PHQ-9 scores as the strongest predictor, which validates the model's clinical utility by acknowledging the chronic nature of depressive symptoms. However, the emergence of behavioral features (passive use) and sleep-related features (latency) as primary predictors, alongside psychological traits, confirms that modifiable lifestyle factors play a substantial role in the trajectory of adolescent depression. The machine learning approach effectively handled the nonlinear interactions within the EMA data, reinforcing the DSEM findings in a complementary predictive framework.

Limitation

Several methodological considerations warrant acknowledgment. First, reliance on self-reported assessments for social media engagement, emotional states, and sleep patterns introduces the potential for recall inaccuracies and social desirability effects. Although the use of EMA minimizes retrospective bias related to traditional surveys, prior work indicates that self-reported digital media use aligns only weakly with passively logged data, suggesting the need for future studies incorporating objective tracking methods such as passive sensing or screenshot-based validation. Second, the use of convenience sampling restricts the generalizability of our findings, and the exclusion of participants with low EMA response rates may have introduced selection bias if those excluded differed systematically from the retained sample. Third, the lack of formal power calculations and adjustments for multiple testing may have elevated the risk of both false-positive and false-negative findings, given the number of statistical comparisons performed. Fourth, the potential for reverse influences, particularly the possibility that NA could increase passive scrolling, was not formally examined. Moreover, although our mediation models were designed to respect temporal ordering, the observational design precludes causal interpretation. Fifth, the modified PANAS and the study-specific EMA items lack formal psychometric validation, though they were adapted from established tools and demonstrated acceptable reliability in this cohort. Sixth, the random forest model is constrained by the modest sample size, the use of a single train-test split, the absence of external validation, and the potential for overfitting; additionally, variable importance estimates derived from MDI may be biased toward features with particular distributional properties. Seventh, potential clustering of participants within schools or youth centers was not fully accounted for, which may have influenced the independence of observations. Eighth, several relevant confounders including family functioning, peer relations, bullying exposure, parental monitoring, and baseline anxiety were not measured or controlled. Lastly, the PSQI assesses sleep over a one-month period, whereas the EMA protocol spanned 21 days; while the PSQI remains suitable as a baseline trait measure, this discrepancy in recall intervals should be considered when interpreting its association with daily EMA-derived sleep indices.

Conclusion

This study provides a nuanced understanding of the digital determinants of adolescent mental health. The evidence demonstrates that it is not the duration of social media use per se, but the interplay of passive consumption, individual susceptibility (FoMO), and sleep disruption that drives depressive symptoms. Passive scrolling was prospectively associated with emotional distress and sleep disruption, even after accounting for baseline depressive symptoms. These findings suggest that modifiable behavioral and sleep factors may contribute to the trajectory of depressive symptoms in this community sample of adolescents. In contrast, active interaction appears to be an emotionally neutral or even positive behavior. These findings advocate for a paradigm shift in public health guidelines: moving away from blanket screen-time restrictions toward specific behavioral interventions. Clinicians and educators should prioritize helping adolescents modify how they use social media (reducing passive scrolling and managing FoMO) and strictly limit nighttime use to protect sleep hygiene. By targeting these specific modifiable mechanisms, we can leverage the digital world to support rather than undermine adolescent psychological well-being.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Author’s Contributions

“SM” Conceptualization, methodology, data curation, formal analysis, investigation, and writing—original draft. “KM” Data collection, investigation, and writing—review and editing. “JM” Investigation, data curation, and writing—review and editing. “TI” Data collection, formal analysis, and investigation. “OM” Data curation, investigation, and writing—review and editing. “RI” Methodology, formal analysis, and validation. “TG” Investigation, data collection, and validation. “KS” Data curation, investigation, and writing—review and editing. “EI” Supervision, validation, and writing—review and editing. “SM” Project administration and correspondence.

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