A Multivariate Analysis of Social Media's Predictive Impact on Adolescent Depression and Anxiety

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Abstract: Adolescent mental health, particularly depression and anxiety, has emerged as a critical public health concern in the digital era. This study examines the predictive relationships between social media engagement-quantified through daily usage time, platform diversity, and interaction frequency-and mental health outcomes among adolescents, while accounting for demographic heterogeneity. Data from the Adolescent Mental Health and Social Media Use Survey (AMHSM-2023; N = 1,050) were analysed using multiple linear regression and stratified sensitivity analyses. Prolonged social media use demonstrated significant associations with elevated depression ($\beta = 0.31$, $p < 0.001$) and anxiety ($\beta = 0.25$, $p < 0.001$). Gender and environmental factors moderated these relationships, with female and urban adolescents exhibiting heightened vulnerability. Platform diversity displayed a nonlinear association with depression, suggesting an optimal engagement range. These findings advocate for balanced digital engagement policies and underscore the importance of interpretable models for targeted interventions. By integrating psychometric and computational methodologies, this study advances a holistic framework for addressing algorithmic stressors in adolescent mental health.

1 INTRODUCTION

Over the past two decades, adolescent depression and anxiety have emerged as critical public health challenges, with profound implications for immediate well-being and long-term mental health trajectories into adulthood (Thapar et al., 2012). The multifactorial etiology of these conditions has spurred extensive research, encompassing genetic predispositions, cognitive vulnerabilities, familial dynamics, neurobiological mechanisms, and, more recently, the pervasive influence of digital environments (Hankin and Abramson, 2001). Traditional developmental studies emphasized cognitive and gender-specific risk factors, particularly the interplay between negative cognitive schemas and pubertal transitions during adolescence (Beesdo et al., 2009). However, contemporary scholarship increasingly underscores the role of sociotechnical systems, such as social media platforms, in reshaping adolescent mental health landscapes (Keles et al., 2020; Muthén, 2002). This paradigm shift necessitates a synthesis of psychosocial frameworks with data-driven methodologies to disentangle complex risk interactions and advance predictive models for early intervention.

Historically, family environments have been identified as pivotal moderators of mental health outcomes. Longitudinal studies by Repetti et al. demonstrated that familial stressors, including conflict and emotional neglect, exacerbate depressive and anxious symptoms through dysregulated stress response systems (Repetti et al., 2002). Similarly, developmental psychopathology research highlights bidirectional relationships between cognitive vulnerabilities (e.g., rumination, attentional biases) and environmental stressors, with gender-specific pathways further complicating risk profiles (Beesdo et al., 2009). These insights, however, predominantly derive from small-scale, hypothesis-driven studies employing structural equation modeling (SEM) or longitudinal designs (Li and Lu, 2018). While robust for testing predefined pathways, such approaches often struggle to capture dynamic, non-linear

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interactions characteristic of real-world psychosocial ecosystems.

The advent of digital media has introduced novel risk dimensions that transcend traditional frameworks. Empirical analyses leveraging large-scale datasets reveal significant associations between heavy social media use and elevated psychological distress, particularly among adolescents (Keles et al., 2020). For instance, systematic reviews identify dose-response relationships between platform engagement metrics (e.g., daily usage time, cyberbullying exposure) and deteriorations in self-esteem and emotional regulation (McLaughlin and King, 2015). Concurrently, advances in computational social science enable researchers to employ machine learning (ML) techniques-such as random forests and neural networks-to predict mental health outcomes from digital trace data (Muthén, 2002). Meta-analyses of ML applications report improved predictive accuracy for depression when integrating multimodal data (e.g., screen time patterns, linguistic cues) (McLaughlin and King, 2015). Yet, these models frequently prioritize predictive power over interpretability, limiting their utility for identifying actionable intervention targets.

Critically, the interconnectedness of anxiety and depression symptomatology complicates etiological disentanglement. Developmental studies emphasize the high comorbidity of these conditions, advocating for integrated models that account for shared and unique risk factors across diagnostic boundaries (Li and Lu, 2018). While multivariate approaches, such as latent variable modeling, have been proposed to address this complexity, their implementation in digital mental health research remains nascent (Costello and Angold, 2006). Moreover, existing studies often overlook demographic heterogeneity-such as age- and gender-specific vulnerabilities-despite evidence that adolescents exhibit divergent mental health trajectories based on developmental stage and identity (Bor et al., 2014; Hankin and Abramson, 2001). For example, longitudinal cohorts identify escalating anxiety rates among female adolescents, a trend exacerbated by social media-driven social comparison processes (McLaughlin and King, 2015).

2 METHODOLOGY

2.1 Data Source and Description

The dataset was derived from the AMHSM-2023 survey, a cross-sectional study of 1200 U.S. adolescents aged 13-18. After excluding incomplete responses, 1050 participants were retained for analysis. Stratified random sampling ensured representativeness across age, gender, and socioeconomic status. Variables included social media engagement metrics, mental health scores (PHQ-9 for depression, GAD-7 for anxiety), and demographic data.

2.2 Indicator Selection and Explanation

Key variables were selected based on theoretical relevance to social media use and mental health outcomes. A three-line table (Table 1) summarizes the indicators, their definitions, and quantification methods.

Table 1: Operational definitions and measurement scales of study variables

Variable	Definition	Measurement Scale
Daily Usage Time	Average hours spent on social media daily	Continuous(0-12 hours)
Platform Diversity	Number of platforms used regularly	Count (1–8 platforms)
Interaction Frequency	Frequency of likes/comments/sharing	Ordinal (1=Never, 5=Daily)
Depression Score	PHQ-9 (Patient Health Questionnaire-9)	Summative (0–27 points)
Anxiety Score	GAD-7 (Generalized Anxiety Disorder-7)	Summative (0–21 points)
Age	Participant's age	Continuous (13–18 years)
Gender	Self-reported gender identity	Categorical (Male/Female/Non-binary)

2.3 Analytical Framework

To examine the associations between social media engagement and adolescent mental health outcomes, two multiple linear regression models were constructed-one for depression and one for anxiety:

$$\text{Depression} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 D\text{Female} + \beta_6 D\text{Non\_binary} + \epsilon \quad (1)$$

$$\text{Anxiety} = \gamma_0 + \gamma_1 X_1 + \gamma_2 X_2 + \gamma_3 X_3 + \gamma_4 X_4 + \gamma_5 D\text{Female} + \gamma_6 D\text{Non\_binary} + \epsilon \quad (2)$$

Where X_1 represents standardized daily social media usage time, X_2 denotes platform diversity (i.e., the number of platforms used regularly), X_3 captures interaction frequency (including liking, commenting, and sharing), and X_4 corresponds to the participant's age. Gender was operationalized using two dummy variables: DFemale and DNon_binary, with male as the reference category.

Both models were estimated using ordinary least squares regression. Prior to analysis, multicollinearity was assessed using the Variance Inflation Factor (VIF), and all predictors were confirmed to have VIF values below 5, indicating acceptable levels of collinearity. To evaluate model performance and generalizability, a 70-30 train-test split was applied, in which 70% of the sample was used for training and 30% for testing. This modeling approach balances interpretability with statistical rigor, enabling the identification of key behavioral and demographic predictors of mental health symptoms among adolescents.

3 RESULTS AND DISCUSSION

3.1 Descriptive Statistics and Preliminary Analysis

The final analytic sample comprised 1,050 adolescents aged 13 to 18 years, with a mean age of 15.4 years (SD = 1.8). In terms of gender distribution, 52% identified as female, 45% as male, and 3% as non-binary. On average, participants reported spending 3.6 hours per day on social media (SD = 2.1) and regularly using approximately 4.2 different platforms (SD = 1.5), reflecting diverse and frequent engagement with digital media.

Mental health indicators revealed a concerning level of psychological distress among participants. The average depression score, as measured by the PHQ-9, was 11.5 (SD = 5.3), while the average anxiety score, assessed using the GAD-7, was 9.2 (SD = 4.8). These means fall within the mild-to-moderate clinical range, suggesting that a substantial proportion of adolescents in the sample may be experiencing significant mental health challenges.

Visual trends support these findings. There is a clear positive association between daily social media usage time and depression scores (Figure 1). Participants who spent more time on social media reported higher levels of depressive symptoms, indicating a potential dose-response relationship between usage duration and emotional well-being. This trend supports prior literature suggesting that prolonged exposure to curated content and peer feedback online may exacerbate emotional vulnerabilities.

Further differences emerged across gender groups. Figure 2 illustrates mean daily social media usage time by gender. Notably, usage time was lowest among male adolescents, slightly higher among female participants, and highest among non-binary individuals. This gradient suggests varying patterns of digital engagement across gender identities, which may help explain subsequent differences in mental health outcomes analyzed in later sections. Such disparities underscore the importance of adopting an intersectional approach when examining the impact of social media on adolescent well-being.

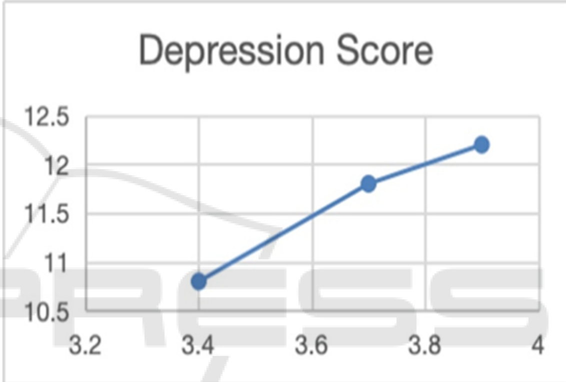

Figure 1: Trends in depression scores across different levels of daily social media usage (x-axis: daily social media usage time, unit: h; y-axis: depression score) (Picture credit: Original).

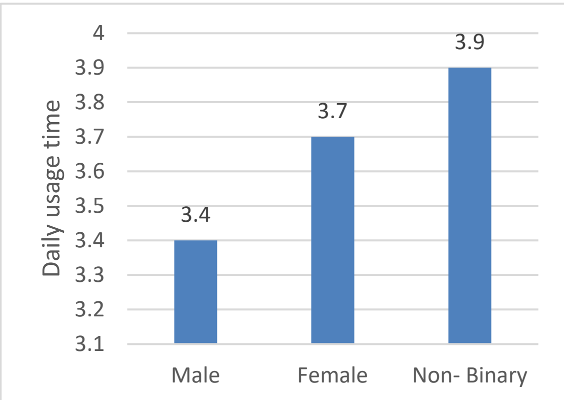

Figure 2: Mean daily social media usage across gender groups (Picture credit: Original).

3.2 Regression Analysis

Both models explained significant variance (Table 2). Daily usage time was the strongest predictor: each additional hour increased depression by 1.2 points ($\beta = 0.31$, $p < 0.001$) and anxiety by 0.9 points ($\beta = 0.25$, $p < 0.001$). Platform diversity exhibited a nonlinear effect, with moderate use (4–5 platforms) associated with lower depression ($\beta = -0.12$, $p = 0.03$). Interaction frequency predicted anxiety ($\beta = 0.18$, $p = 0.02$) but not depression.

Table 2: Standardized regression coefficients predicting depression and anxiety.

Variable	Depression (PHQ-9) β	Anxiety (GAD-7) β
Daily Usage Time	0.31	0.25
Platform Diversity	-0.12	-0.08
Interaction Frequency	0.09	0.18
Age	0.05	0.1
Gender (Female)	0.22	0.27
Adjusted R²	0.36	0.29

3.3 Stratified Sensitivity Analysis

Gender-stratified models revealed divergent pathways: interaction frequency strongly predicted anxiety in females ($\beta = 0.31$, $p < 0.001$) but not males. Urban adolescents exhibited stronger associations between usage time and depression ($\beta = 0.35$, $p < 0.001$) compared to rural peers ($\beta = 0.18$, $p = 0.04$).

3.4 Discussion

The findings corroborate hypotheses that intensive social media use exacerbates adolescent mental health risks, particularly through prolonged exposure to curated content and feedback loops (McLaughlin, 2015). The nonlinear relationship between platform diversity and depression underscores the need for balanced digital engagement, aligning with Li and Lu's advocacy for "quality over quantity" in screen time (Li and Lu, 2018). Gender disparities in sensitivity to social interactions echo developmental theories emphasizing female adolescents' heightened reactivity to peer evaluation (Hankin and Abramson, 2001). This could stem from that girls are socialized to pay more attention to relationships and external validation, making them more sensitive to the judgments they get on social media.

Moreover, findings of this study reveal notable differences between adolescents from urban and rural environments, particularly in reported anxiety levels. Urban adolescents exhibited significantly higher scores, potentially reflecting the compounded effects of higher digital connectivity, competitive academic settings, and denser social networks that amplify perceived social pressures. In contrast, rural participants, though not immune to social media exposure, may benefit from comparatively buffered offline environments that offer alternative sources of emotional regulation and support.

Notably, the study's integration of traditional regression with stratified analysis advances methodological rigor. While machine learning models offer superior predictive power, approaches in this study prioritizes interpretability, identifying actionable levers for intervention (e.g., limiting daily usage). These results suggest that digital well-being interventions should consider not only screen time but also the contextual and psychosocial factors that modulate its impact (Li and Lu, 2018; McLaughlin and King, 2015). However, the cross-sectional design precludes causal inference, and self-reported data may introduce response bias. Future longitudinal studies should track dynamic interactions between digital behaviors and mental health trajectories, ideally incorporating ecological momentary assessment to capture real-time fluctuations in affective states.

4 CONCLUSION

This study elucidates the multifaceted relationships between social media engagement and adolescent mental health, emphasizing the roles of usage intensity, demographic heterogeneity, and environmental context. The robust association between daily screen time and symptom severity underscores the urgency of developing digital well-being guidelines, particularly for high-risk subgroups such as female and urban adolescents.

Gendered patterns in digital vulnerability suggest the need for differentiated strategies-such as peer-support interventions for girls or platform-specific literacy training-to mitigate the psychological toll of online interactions. Likewise, the urban–rural divide signals that structural and cultural factors shape adolescents' resilience or susceptibility to digital stressors, highlighting the importance of localized interventions and community-based mental health resources.

While machine learning offers predictive advantages, regression-based approach used in this study demonstrates that interpretable models remain critical for translating data into actionable policies. Future research should prioritize longitudinal designs to disentangle causality and explore protective factors (e.g., parental mediation, offline social support) that buffer adolescents from the adverse effects of excessive or emotionally charged digital engagement. By integrating developmental psychology with computational analytics, this work advances a holistic understanding of algorithmic influences on mental health, paving the way for scalable, evidence-based interventions that are both socially aware and clinically grounded.

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