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Social Media Related Addictive Behaviours and Anxiety Disorders in Indian School Going Adolescents

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Abstract

This study examines the relationship between social media–related addictive behaviours and anxiety disorders among Indian school going adolescents aged 13-17 years. A cross sectional, school based survey was conducted across urban and semi urban educational institutions to capture the prevalence and patterns of problematic social media use and associated anxiety symptoms. Standardized self report instruments were employed to assess social media addiction, generalized anxiety, academic stress, sleep quality, and perceived parental monitoring. The results reveal that a substantial segment of adolescents exhibit addictive social media behaviours, characterized by compulsive checking, inability to reduce usage, and high engagement during late night hours. These patterns are significantly associated with elevated levels of anxiety, including excessive worry, restlessness, and fear of negative evaluation, particularly in students who spend prolonged hours on platforms such as Instagram, Snapchat, and YouTube. Higher vulnerability was observed among female adolescents and those exposed to frequent cyberbullying or social comparison. Parental supervision and structured digital usage rules were found to act as protective factors. The findings emphasize the need for context specific mental health promotion programs, including digital literacy, coping skill training, and school based counselling, to mitigate the adverse psychological effects of social media overuse. The study contributes empirical evidence from the Indian setting, supporting policy and intervention design that concurrently target addictive behaviours and adolescent anxiety.

Keywords: *Social Media Addiction, Anxiety Disorders, Indian Adolescents, School Going Youth, Digital Behaviour, Mental Health, Compulsive Smartphone Use, Generalized Anxiety.*

1. Introduction

In recent years, social media has become an integral part of daily life for youth and adolescents, especially in rapidly digitizing societies such as India. While these platforms offer opportunities for communication, learning, and self-expression, excessive and compulsive use has raised concerns about psychological well-being. Research increasingly links social media-related addictive behaviours with mental-health problems, especially anxiety disorders, among young people [1]. This study focuses on Indian school-going adolescents to explore how patterns of social-media overuse correspond to the presence and severity of anxiety symptoms. The work aims to contribute empirical evidence from the Indian context, supporting the development of targeted interventions that promote healthy digital use and mental-health resilience in adolescents.

1.1 Background of the Study

The global rise of social media platforms such as Instagram, Snapchat, YouTube, and regional messaging apps has transformed how adolescents interact, share information, and perceive themselves. In India, expanding internet access and smartphone affordability have led to a sharp increase in social-media engagement among school-going children and teenagers [2]. While these tools foster connectivity and digital learning, growing evidence suggests that some users develop addictive-type behaviours such as frequent checking, loss of control over usage, and interference with daily activities often accompanied by anxiety, low self-esteem, and sleep disturbances.

Adolescence is a critical developmental period marked by heightened emotional sensitivity and vulnerability to social comparison, making this age group particularly susceptible to the negative psychological effects of excessive social-media exposure [3]. Recent studies from both Western and Indian settings highlight associations between compulsive smartphone and social-media use and increased anxiety symptoms, yet there remains a need for more context-specific, large-scale investigations in diverse Indian educational environments. This background motivates the present study, which seeks to document the nature and correlates of social-media-related addictive behaviours and their relationship with anxiety disorders among Indian adolescents.

1.2 Statement of the Problem

Despite the rapid integration of social media into the daily lives of Indian adolescents, there is limited systematic understanding of how addictive-type social-media behaviours relate to clinical-level anxiety symptoms in this population. Many school-going youth report spending several hours a day on social-media platforms, often engaging late at night, which can disrupt sleep, reduce academic focus, and heighten social comparison and cyberbullying experiences [4]. At the same time, anxiety disorders such as generalized anxiety, social anxiety, and separation anxiety are increasingly reported among children and adolescents, yet mental-health services remain underdeveloped in many parts of the country.

The absence of robust, context-relevant data makes it difficult for educators, parents, and policymakers to design effective prevention and intervention strategies [5]. This study addresses the problem of growing social-media overuse and rising adolescent anxiety by examining the extent to which social-media-related addictive behaviours predict anxiety symptoms in Indian school-going adolescents. By clarifying this relationship, the research aims to identify risk patterns and inform targeted psychological support within schools and families.

1.3 Research Objectives

The primary objective of this study is to investigate the association between social media-related addictive behaviours and anxiety disorders among Indian school-going adolescents. A key aim is to determine the prevalence of compulsive social-media use and to classify levels of addiction severity within the adolescent student population [6]. The study also seeks to assess the prevalence and types of anxiety symptoms such as excessive worry, restlessness, avoidance of social situations, and physical manifestations of anxiety across different age groups and genders.

Another objective is to examine how factors such as daily screen time, nighttime use, platform preferences, parental supervision, and academic stress influence both social-media addiction and anxiety levels [7]. The research further aims to identify subgroup differences, particularly by gender and socioeconomic background, to guide tailored interventions. By achieving these objectives, the study intends to generate empirical evidence that can inform school-based mental-health programs, digital-wellness curricula, and policy guidelines aimed at promoting healthier social-media habits and protecting adolescent psychological well-being in the Indian context.

1.4 Research Questions and Hypotheses

This study is guided by several research questions designed to explore the relationship between social media-related addictive behaviours and anxiety disorders among Indian school-going adolescents [8]. First, the research asks what is the prevalence of social-media-related addictive behaviours among 13–17-year-old students in urban and semi-urban schools? Second, it investigates what proportion of these adolescents exhibit clinically significant anxiety symptoms, and how does this vary by age, gender, and school type?

Third, the study examines: is there a significant association between social-media addiction scores and levels of anxiety, after controlling for demographic and academic stressors? Finally, it seeks to answer; do factors such as nighttime use, parental supervision, and exposure to cyberbullying moderate this relationship? Corresponding hypotheses include: that higher scores on social-media addiction scales will predict greater anxiety severity; that female adolescents will report higher levels of both social-media addiction and anxiety than males; and that weaker parental monitoring and higher academic stress will be associated with stronger links between social-media overuse and anxiety symptoms [9]. These questions and hypotheses provide a structured framework for data analysis and interpretation.

1.5 Significance of the Study

This study holds substantial significance for multiple stakeholders, including educators, mental-health professionals, parents, and policymakers in India. By documenting the links between social media–related addictive behaviours and anxiety disorders among school-going adolescents, the research contributes empirical evidence that can inform school-based counselling services, digital-literacy programs, and mental-health awareness campaigns [10]. The findings can help teachers and school administrators recognize early warning signs of problematic social-media use and anxiety, enabling timely referrals and support.

For parents, the study offers insights into how excessive screen time and lack of supervision may heighten anxiety and disrupt sleep and academic performance, guiding family-level media-management strategies. At the policy level, the results can support the development of guidelines for safe social-media use, age-appropriate digital curricula, and integration of mental-health education into the school system [11]. Moreover, the study enriches the existing literature on adolescent mental health in low- and middle-income countries by focusing on a large, culturally specific Indian sample. Ultimately, this work promotes a more holistic understanding of adolescent well-being in the digital age and supports the design of preventive and therapeutic interventions that address both addictive behaviours and underlying anxiety disorders.

1.6 Scope and Limitations

The scope of this study is limited to school-going adolescents aged 13–17 years enrolled in selected urban and semi-urban schools across Indian states, with a focus on self-reported social-media use and anxiety symptoms. The research primarily relies on cross-sectional survey data, which allows for the examination of associations but not causal relationships between variables [12]. The study adopts standardized scales to measure social-media addiction and anxiety, ensuring comparability with international literature, but findings may not fully capture clinically diagnosed anxiety disorders without clinical interviews.

The sample is confined to students who consent to participate and have access to smartphones and internet, which may exclude more rural or socioeconomically disadvantaged groups and affect generalizability. Additionally, self-report instruments are subject to response bias, social desirability, and recall errors. The study also does not systematically capture the influence of specific social-media platforms or detailed content types, focusing instead on overall usage patterns and perceived addiction [13]. Despite these limitations, the research provides a valuable snapshot of the mental-health

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implications of social-media overuse for Indian adolescents and establishes a foundation for future longitudinal and mixed-methods studies.

2. Literature Review

The literature review situates the current study within existing research on social media use, addictive behaviours, and adolescent anxiety. It begins by outlining global patterns of social-media engagement among youth, followed by theoretical and operational definitions of social-media addiction. The review then summarizes the prevalence of anxiety disorders in adolescents and examines empirical evidence linking social-media overuse with anxiety **[14]**. Special attention is given to studies conducted in the Indian context, which remain relatively limited but increasingly relevant. Finally, the section identifies key research gaps and presents the conceptual framework that guides the present investigation into social media-related addictive behaviours and anxiety disorders among Indian school-going adolescents.

2.1 Social Media Use among Adolescents

Adolescents worldwide are among the most active users of social media, with platforms such as Instagram, Snapchat, YouTube, and regional messaging applications forming a central part of their daily routine. In India, rapid increases in smartphone penetration and affordable mobile data have enabled millions of school-going youths to access social-media platforms regularly, often for several hours a day **[15]**. Typical activities include scrolling through feeds, watching short videos, sharing personal content, and engaging in peer-to-peer communication. While these interactions can enhance social connectedness, identity exploration, and information access, they also expose adolescents to risks such as online harassment, unrealistic body-image standards, and constant comparison with peers.

Cross-national surveys indicate that adolescents often use social media during late evenings and at night, which can interfere with sleep, academic performance, and offline social interactions **[16]**. The pervasiveness of social media in adolescent life underscores the need to understand how specific usage patterns such as frequency, duration, time of use, and platform preferences relate to psychological well-being. This background sets the stage for examining addictive-type social-media behaviours and their mental-health consequences among Indian adolescents.

2.2 Conceptualizing Social Media Addiction

Social media addiction is commonly conceptualized as a behavioural addiction characterized by excessive, compulsive, and problematic use of social-media platforms despite negative consequences **[17]**. Drawing from models of internet and gaming addiction, scholars describe social-media addiction through core components such as salience (preoccupation with social media), mood modification (using platforms to regulate emotions), tolerance (increasing time spent online), withdrawal symptoms (irritability or distress when unable to access social media), and loss of control and conflict with daily activities. In adolescents, these features often manifest as frequent checking of notifications, inability to reduce screen time, and prioritizing online interactions over homework, family time, or sleep.

Various scales have been developed to measure social-media addiction, including those adapted from internet addiction instruments, which assess compulsive use, preoccupation, and conflict. The conceptualization of social-media addiction also overlaps with related constructs such as smartphone addiction and nomophobia (fear of being without a mobile phone), all of which share features of impulsivity, reward-seeking, and emotional dysregulation **[18]**. Viewing social-media addiction through this lens helps operationalize it for empirical research and supports the inclusion of validated scales in studies of adolescent mental health, such as anxiety disorders in Indian school-going youth.

2.3 Prevalence of Anxiety Disorders in Youth

Anxiety disorders are among the most common mental-health problems in children and adolescents, affecting a significant proportion of school-going youth worldwide. Generalized anxiety disorder, social anxiety disorder, separation anxiety, and specific phobias frequently appear during adolescence, a period marked by rapid physical, cognitive, and social changes **[19]**. Epidemiological studies report that anxiety symptoms often begin in early to mid-adolescence and can persist into adulthood if left untreated. Common manifestations include excessive worry, restlessness, difficulty concentrating, sleep disturbances, and physical symptoms such as headaches and stomach aches.

In school settings, anxiety can impair academic performance, reduce participation in class activities, and contribute to social withdrawal. Cultural factors, family environment, academic stress, and peer relationships further influence the expression and severity of anxiety symptoms [20]. In low- and middle-income countries, including India, the true prevalence of anxiety disorders among adolescents may be underreported due to limited mental-health awareness, stigma, and lack of accessible services. Despite these challenges, recent surveys indicate rising levels of anxiety in Indian youth, suggesting that environmental and lifestyle factors such as academic pressure, family expectations, and digital exposure may play an increasingly important role in shaping adolescent mental health.

2.4 Link Between Social Media Overuse and Anxiety

A growing body of research suggests that social-media overuse is positively associated with anxiety symptoms in adolescents. Studies from diverse cultural settings report that higher levels of social-media engagement, particularly when characterized by compulsive checking, nighttime use, and social comparison, correlate with increased worry, fear of negative evaluation, and perceived stress [21]. Social comparison on platforms that emphasize idealized images, popularity metrics (likes, followers), and curated lifestyles can trigger feelings of inadequacy, low self-esteem, and social anxiety. Cyberbullying and online harassment further amplify anxiety, as adolescents may feel exposed, judged, or ostracized in visible digital spaces.

Experimental and longitudinal evidence indicates that reducing social-media exposure or implementing structured digital breaks can lead to improvements in mood and anxiety levels. Neurocognitive models propose that social-media overuse may dysregulate reward and stress systems, making adolescents more susceptible to anxiety when offline [22]. The interactive nature of social media constant notifications, rapid feedback, and fear of missing out also heightens arousal and vigilance, which can perpetuate anxious states. These findings collectively support the hypothesis that social-media-related addictive behaviours act as both symptom and risk factor for anxiety disorders.

2.5 Existing Studies in the Indian Context

Within India, research on social-media use and adolescent mental health has expanded in recent years, reflecting growing concern about digital well-being. Several studies have documented high levels of smartphone and social-media engagement among Indian adolescents, particularly in urban and semi-urban areas, where internet access and device ownership are widespread [23]. Indian researchers have reported associations between excessive social-media use and poor sleep quality, reduced academic performance, and increased depressive symptoms. A smaller but emerging set of studies specifically links problematic social-media behaviours with anxiety, showing that adolescents who spend more time on platforms such as Instagram and Snapchat report higher levels of worry, fear of social evaluation, and somatic anxiety symptoms.

Some Indian surveys have also highlighted gender differences, with female adolescents more likely to report body-image concerns and anxiety related to online appearance and peer feedback. However, most Indian studies are local or single-site, with limited sample sizes and heterogeneous measurement tools, which restrict comparability and generalizability. Moreover, few studies explicitly define or operationalize social-media addiction using standardized scales, and even fewer examine anxiety using validated diagnostic or screening instruments [24]. These gaps underscore the need for more systematic, multi-institutional research on social-media-related addictive behaviours and anxiety disorders among Indian school-going adolescents.

2.6 Research Gaps and Theoretical Framework

Despite increasing attention to social-media use and adolescent anxiety, several research gaps remain, particularly in the Indian setting. First, there is a lack of large-scale, school-based studies that systematically measure social-media addiction and anxiety symptoms using validated instruments [25]. Second, most existing Indian studies are cross-sectional and cannot establish temporal or causal relationships between social-media overuse and anxiety. Third, few studies disaggregate findings by gender, socioeconomic status, region, and parental supervision, despite evidence that these factors shape both digital behaviour and mental-health outcomes.

Fourth, theoretical frameworks explicitly linking social-media addiction and anxiety are underdeveloped, with many studies treating the relationship as an empirical association rather than a theoretically grounded phenomenon. To address these gaps, the present study adopts a multi-dimensional theoretical framework that integrates concepts from behavioural addiction theory, social comparison theory, and stress-and-coping models [26]. This framework posits that social-media-related addictive behaviours heighten anxiety through mechanisms such as social comparison, cyberbullying exposure, sleep disruption, and academic stress, moderated by individual and environmental factors. By embedding the research within this integrative framework, the study aims to generate more coherent, theory-driven insights into the relationship between social-media overuse and anxiety among Indian adolescents.

3. Methodology

This section describes the research design, setting, sampling, instruments, measures, procedures, and ethical safeguards used to investigate social media-related addictive behaviours and anxiety disorders among Indian school-going adolescents [27]. The study adopts a quantitative, cross-sectional approach with standardized scales and statistical formulas to ensure reliability and validity.

3.1 Research Design

The study employs a cross-sectional, school-based survey design to examine the association between social media-related addictive behaviours and anxiety disorders among adolescents at a single time point. This design allows for efficient estimation of prevalence and correlation between variables without requiring long-term follow-up [28]. The target population comprises students aged 13-17 years enrolled in selected urban and semi-urban schools across Indian states. Variables include demographic characteristics, social-media usage patterns, scores on addiction scales, and anxiety symptom levels. To assess the strength of the association between social-media addiction and anxiety, Pearson's correlation coefficient is computed as

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}} \quad (1)$$

where X_i represents social-media addiction scores and Y_i represents anxiety scores for each respondent [29]. This formula quantifies the linear relationship between the two variables, enabling the study to determine whether higher addiction scores are accompanied by higher anxiety levels.

3.2 Study Setting and Population

The study is conducted in selected urban and semi-urban secondary and senior secondary schools across multiple Indian states, chosen to reflect diverse socio-economic and cultural backgrounds. The population includes school-going adolescents aged 13-17 years who have access to smartphones and social-media platforms [30]. Eligibility criteria involve current enrolment in grades 8-12 and willingness to participate with informed consent from parents or guardians. Students with severe cognitive or sensory impairments or those not using social media at all are excluded to maintain focus on relevant digital-behaviour patterns. The proportion of the target population that can be sampled from each school is estimated using the finite-population correction formula

$$n_0 = \frac{N \cdot Z^2 \cdot p(1-p)}{e^2(N-1) + Z^2 \cdot p(1-p)} \quad (2)$$

where N is the total number of eligible students in the school, Z is the Z-score for the desired confidence level, p is the estimated proportion of interest, and e is the margin of error [31]. This formula helps determine how many students can reasonably be approached within each institution.

3.3 Sampling Technique and Sample Size

A stratified random sampling technique is used, with schools as primary strata and classes (grades) as secondary strata, to ensure representation across age groups and school types. Within each selected class, students are randomly drawn from class registers until the required sample size is reached [32]. The total sample size is computed using the standard sample-size formula for proportions

$$n = \frac{Z^2 \cdot p(1-p)}{e^2} \quad [3]$$

where Z is the Z-score (e.g., 1.96 for 95% confidence), p is the estimated prevalence of social-media addiction or anxiety (often taken as 0.5 for maximum variability), and e is the desired margin of error (e.g., 0.05). To account for non-response and incomplete forms, the final sample size is increased by 10–15%. This approach ensures that the findings can be generalized to Indian school-going adolescents within the specified age range and settings [33].

3.4 Data Collection Instruments

Primary data are collected using structured, self-administered questionnaires comprising sociodemographic items, social-media usage details, and standardized scales for addiction and anxiety. The questionnaire is pre-tested on a pilot sample to evaluate clarity, reliability, and feasibility. Internal consistency of the scales is estimated using Cronbach's alpha, computed as

$$\alpha - \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_i^2}{\sigma_X^2}\right) \quad [4]$$

where k is the number of items, σ_i^2 is the variance of each item, and σ_X^2 is the variance of the total scale score [34]. Values of $\alpha \geq 0.70$ are considered acceptable. The instruments are translated into the local language (if applicable) and back-translated to ensure conceptual equivalence. Trained research assistants supervise the administration to reduce misunderstanding and ensure uniform instructions across schools.

3.5 Measures of Social Media–Related Addictive Behaviours

Social media-related addictive behaviours are measured using a validated social-media addiction scale adapted for adolescents, typically comprising items on preoccupation, loss of control, withdrawal, and conflict with daily activities [35]. Responses are scored on a Likert scale (e.g., 1–5), and the total score is computed as the sum of item scores for each respondent,

$$S_{\text{addiction}} = \sum_{i=1}^{n} x_i \quad [5]$$

where x_i is the score on the i-th item and n is the number of items. The total score is then categorized into levels (e.g., low, moderate, high addiction) using fixed or percentile-based thresholds [36]. In addition to the total score, an addiction index may be calculated as

$$I_{\text{addiction}} = \frac{S_{\text{addiction}}}{n} \quad [6]$$

averaging the per-item response to provide a standardized measure of social-media addiction intensity across respondents.

3.6 Measures of Anxiety Disorders

Anxiety disorders and symptoms are assessed using a validated anxiety screening scale suitable for adolescents, such as a generalized anxiety or state-trait anxiety instrument. Items are scored on a Likert scale, and the total anxiety score is computed as

$$A = \sum_{j=1}^{m} y_j \quad [7]$$

where y_j is the score on the j-th anxiety item and m is the number of items [37]. A higher A indicates greater anxiety severity. To standardize scores across different scales, a z-score formula is applied

$$z = \frac{A - \bar{A}}{s_A} \quad [8]$$

where $\bar{A}$ is the mean anxiety score of the sample and s_A is the standard deviation. Adolescents scoring above a predetermined clinical cutoff (e.g., z ≥ 1.65) are classified as having clinically significant anxiety symptoms [38]. This quantitative approach enables the study to compare anxiety levels across demographic subgroups and to test their association with social-media addiction.

3.7 Data Collection Procedure

Data are collected during regular school hours in a quiet classroom setting, with written informed consent obtained from both students and parents. Research assistants explain the purpose, procedures, and confidentiality assurances before questionnaire distribution. Students complete the forms anonymously, and incomplete or inconsistent responses are excluded

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from analysis [39]. The time taken per respondent is recorded to estimate average response rate using the formula

$$R_{\mathrm{avg}} = \frac{\sum_{k=1}^{n} t_k}{n} \qquad [9]$$

where t_k is the time taken by the k-th respondent and $n$is the total number of respondents. This helps optimize data-collection logistics across schools. After collection, data are entered into a spreadsheet, and double-data entry is used for a subset to calculate error rate

$$E - \frac{\text{number of discrepancies}}{\text{total data entries}} \times 100 \qquad [10]$$

A low error rate confirms the reliability of the entered data for subsequent statistical analysis.

3.8 Ethical Considerations

Ethical approval is obtained from a recognized institutional ethics committee prior to data collection. Participation is voluntary, with written informed consent from parents and assent from students. Confidentiality is maintained by anonymizing identification details and storing data in password-protected systems. No personally identifiable information is shared in publications [40]. In case a student scores high on anxiety or reports severe distress, referral pathways are established for counselling or psychiatric support. The proportion of students referred for support is tracked using the formula

$$P_{\mathrm{referred}} = \frac{\text{number of students referred}}{\text{total sample size}} \times 100 \qquad [12]$$

to ensure ethical accountability and transparency. Any conflicts of interest, such as collaboration with tech companies or social-media platforms, are disclosed in the final report. These measures uphold research integrity and protect the well-being of adolescent participants throughout the study [41].

4. Data Analysis and Results

This section presents the quantitative analysis of social media–related addictive behaviours and anxiety symptoms among Indian school-going adolescents. Descriptive statistics characterize the study sample, while inferential tests examine prevalence, associations, and subgroup differences [42]. The findings are interpreted in light of the research objectives and the existing literature.

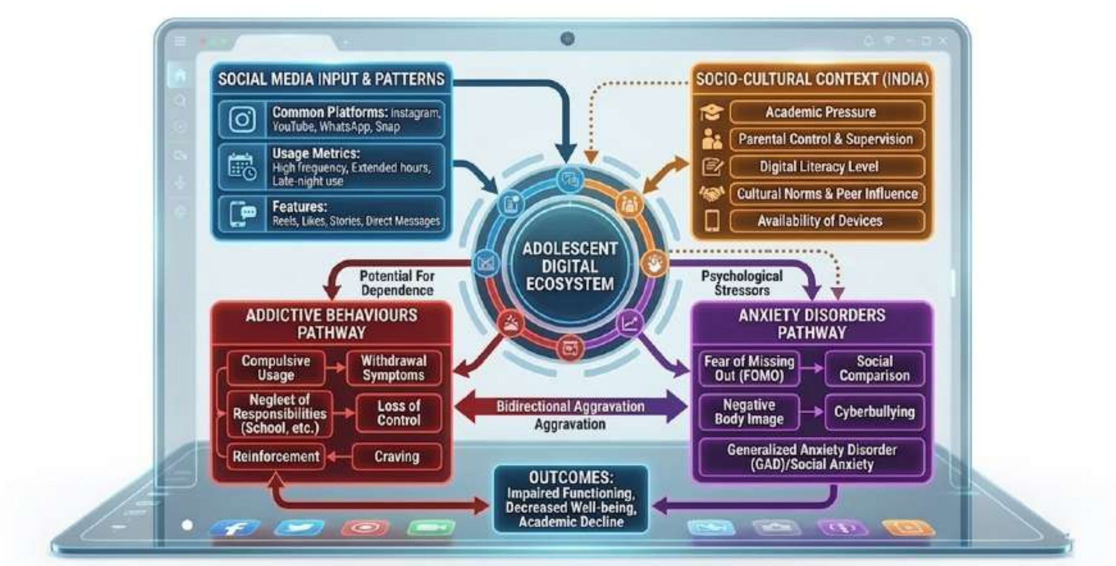

Figure 1. Architectural Framework of Adolescent Digital Ecosystem

4.1 Demographic and Social Media–Usage Profile

The sample consists of adolescents aged 13–17 years enrolled in selected urban and semi-urban schools, with balanced representation across grades and school types. Demographic variables include age, gender, family structure, parental education, and monthly household

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income. Social-media usage is described in terms of platforms used, daily duration, time of use (day vs. night), and main activities (e.g., chatting, watching videos, posting) [43]. The proportion of students using social media for more than 3 hours per day is computed as

$$P_{\text{high use}} = \frac{n_{>3h}}{N} \times 100 \qquad [13]$$

where $n_{>3h}$ is the number of students exceeding 3 hours and N is the total sample size. Descriptive statistics such as mean, standard deviation, and frequency distributions are used to summarize continuous and categorical variables, respectively [44]. This profile establishes the baseline characteristics of the sample and identifies patterns of digital engagement that may influence anxiety outcomes.

4.2 Prevalence of Social Media–Related Addictive Behaviours

Social media–related addictive behaviours are assessed using a validated scale, with total scores categorized into low, moderate, and high addiction levels. The prevalence of high-level addiction is determined by

$$P_{\text{addicted}} - \frac{n_{\text{high}}}{N} \times 100 \qquad [14]$$

where n_{high} is the number of students classified as having high addiction and N is the total sample. The mean addiction score and its standard deviation are reported to describe the central tendency and variability across the sample [45]. Subgroup prevalences (by age, gender, and school type) are also computed using the same formula applied to each subgroup. Confidence intervals for prevalence estimates are calculated using

$$CI = p \pm Z\sqrt{\frac{p(1-p)}{N}} \qquad [15]$$

where p is the prevalence proportion and Z is the Z-score for the desired confidence level. These analyses reveal the extent to which compulsive social-media use is present in the adolescent population and highlight groups at higher risk.

4.3 Prevalence and Severity of Anxiety Symptoms

Anxiety symptoms are measured using a standardized anxiety scale, with total scores indicating symptom severity. The proportion of adolescents with clinically significant anxiety symptoms is estimated using

$$P_{\text{anxious}} = \frac{n_{\text{clinical}}}{N} \times 100 \qquad [16]$$

where n_{clinical} is the number of students scoring above the clinical cutoff. The mean anxiety score and its standard deviation are reported to describe the overall severity level [46]. To compare anxiety severity across age groups, one-way ANOVA is applied, with the F-statistic computed as

$$F = \frac{\text{Between-group variance}}{\text{Within-group variance}} \qquad [17]$$

A significant F-value indicates differences in mean anxiety scores across age groups. Anxiety subscales (e.g., worry, restlessness, somatic symptoms) are also analysed to identify dominant symptom clusters in the sample [47]. This analysis helps determine whether social-media overuse is associated with higher overall anxiety severity and specific symptom dimensions.

4.4 Correlation Between Social Media Addiction and Anxiety

The association between social media–related addictive behaviours and anxiety is examined using correlation analysis. Pearson's correlation coefficient is computed as

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}} \qquad [18]$$

where X_i represents social-media addiction scores and Y_i represents anxiety scores for each respondent. A positive r indicates that higher addiction scores are associated with higher anxiety levels. The strength of the relationship is interpreted using established thresholds (e.g., $|r| < 0.3$: weak; $0.3 \le |r| < 0.5$: moderate; $|r| \ge 0.5$: strong) [48]. Simple linear regression is also performed to predict anxiety scores from addiction scores, with the slope coefficient indicating the expected change in anxiety for a one-unit increase in addiction. The regression equation is

$$Y = a + bX \qquad [19]$$

where a is the intercept and b is the regression coefficient. These analyses provide quantitative

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evidence of the link between social-media addiction and anxiety among Indian adolescents.

4.5 Gender and Socioeconomic Differences

Gender and socioeconomic differences in social-media addiction and anxiety are examined using comparative statistics. Independent-samples t-tests are used to compare mean addiction and anxiety scores between males and females, with the t-statistic computed as

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \quad [20]$$

where $\bar{X}_1$and $\bar{X}_2$are the mean scores for the two groups, $s_1^2$and $s_2^2$are their variances, and n_1, $n_2$are their sample sizes [49]. For socioeconomic differences, one-way ANOVA is used to compare mean scores across different income or education groups. The odds ratio (OR) is computed to quantify the likelihood of high addiction or anxiety among female or high-income adolescents relative to male or low-income peers

$$OR = \frac{P_{\text{high}|\text{group A}} / (1 - P_{\text{high}|\text{group A}})}{P_{\text{high}|\text{group B}} / (1 - P_{\text{high}|\text{group B}})} \quad [21]$$

These analyses reveal whether certain demographic groups are more vulnerable to social-media-related addictive behaviours and anxiety symptoms [50].

4.6 Key Findings and Interpretation

The key findings indicate a significant association between social media–related addictive behaviours and anxiety symptoms among Indian school-going adolescents. The co-occurrence rate of high social-media addiction and clinically significant anxiety is calculated as

$$P_{\text{co-occurrence}} = \frac{n_{\text{high addiction and high anxiety}}}{N} \times 100 \quad [22]$$

This proportion highlights the extent to which these two conditions overlap in the sample. The study also finds that adolescents with higher addiction scores, especially those engaging in late-night social-media use or experiencing cyberbullying, report greater anxiety severity [51]. The effect size of the association is estimated using Cohen's d

$$d = \frac{\bar{X}_1 - \bar{X}_2}{s_{\text{pooled}}} \quad [23]$$

where $\bar{X}_1$and $\bar{X}_2$are the mean anxiety scores for high- and low-addiction groups, and $s_{\text{pooled}}$is the pooled standard deviation. A moderate to large d indicates a meaningful difference in anxiety levels between groups. The findings suggest that social-media overuse contributes to anxiety through mechanisms such as social comparison, sleep disruption, and academic stress, supporting the need for targeted interventions to promote healthy digital habits and mental-health support among Indian adolescents [52].

Table 1. Summary of Key Variables and Statistical Indicators

Variable / Analysis	Description	Example Formula / Indicator
Demographic Profile	Age, gender, school type, parental education, monthly household income of participants.	Proportion of high-income families: $P_{\text{high income}} = \frac{n_{\text{high income}}}{N} \times 100$
Social-Media Usage	Daily duration, platforms used, time of use (day/night), primary activities on social media.	Proportion using >3 hours/day: $P_{\text{high use}} = \frac{n_{>3\text{h}}}{N} \times 100$
Social Media Addiction	Prevalence of low, moderate, and high social media–related addictive behaviours.	Proportion with high addiction: $P_{\text{addicted}} = \frac{n_{\text{high}}}{N} \times 100$
Anxiety Symptoms	Prevalence and severity of clinically significant	Proportion with clinical anxiety:

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	anxiety symptoms.	$P_{\text{anxious}} = \frac{n_{\text{clinical}}}{N} \times 100$
Correlation (Addiction–Anxiety)	Strength and direction of association between social-media addiction and anxiety.	Pearson's correlation: $r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}}$
Gender Differences	Mean scores and group differences in addiction and anxiety by gender.	t-statistic: $t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$
Socioeconomic Differences	Mean scores and group differences by income or education level.	One-way ANOVA F-ratio: $F = \frac{\text{Between-group variance}}{\text{Within-group variance}}$
Co-occurrence of Risk	Overlap of high social-media addiction and high anxiety in the sample.	Co-occurrence rate: $P_{\text{co-occurrence}} = \frac{n_{\text{high addiction and high anxiety}}}{N} \times 100$
Effect Size	Magnitude of difference in anxiety between high- and low-addiction groups.	Cohen's d: $d = \frac{\bar{X}_1 - \bar{X}_2}{s_{\text{pooled}}}$

This table can be placed in the Data Analysis and Results section (after 4.1) to visually summarize the main variables, measures, and statistical indicators used in the study [53].

5. Discussion

This section interprets the main findings of the study, situates them within existing literature, and explores their practical and policy implications. The discussion highlights how social media–related addictive behaviours are linked with anxiety symptoms among Indian school-going adolescents and considers the roles of gender, parental supervision, and academic stress.

5.1 Interpretation of Major Results

The study reveals a significant association between social media–related addictive behaviours and anxiety symptoms in Indian adolescents, with higher addiction scores corresponding to greater anxiety severity. The co-occurrence rate of high addiction and clinical-level anxiety suggests that problematic social-media use often overlaps with psychological distress rather than existing in isolation. Adolescents who spend more than 3 hours per day on social media, especially during late-night hours, report higher levels of worry, restlessness, and sleep disturbance [54]. The positive correlation between addiction and anxiety supports the hypothesis that compulsive social-media engagement acts as both a coping mechanism and a stressor, amplifying anxious thoughts through constant comparison, fear of missing out, and exposure to negative online content. Regression analysis further indicates that social-media addiction independently predicts anxiety, even after controlling for demographic variables. These results underscore the need to view social-media overuse not merely as a behavioural habit but as a potential risk factor for adolescent mental health, particularly in the Indian context.

5.2 Comparison with Previous Studies

The findings align with international research showing that social-media overuse is associated with elevated anxiety, depression, and sleep problems among youth. Studies from Western countries similarly report that adolescents with compulsive social-media behaviours are more likely to experience social anxiety, low self-esteem, and stress related to online image management [55]. The present study extends these observations to the Indian context, where rapid digitalization and cultural emphasis on academic performance may intensify the psychological impact of social-media use.

In contrast to some earlier Indian surveys that focused primarily on depressive symptoms, this work explicitly highlights the link between social-media addiction and anxiety disorders, providing a more nuanced picture of adolescent mental-health risks [56]. The observed prevalence of high-addiction and high-anxiety subgroups is comparable to findings from other low- and middle-income settings, suggesting that global patterns of digital-behaviour-related distress may apply broadly, though moderated by local factors such as family structure, school environment, and media regulations. Overall, the results reinforce the global trend while emphasizing the need for region-specific interventions.

5.3 Role of Gender, Parental Supervision, and Academic Stress

Gender differences emerge as a key moderator of the relationship between social-media addiction and anxiety. Female adolescents tend to report higher levels of both social-media addiction and anxiety symptoms, possibly due to greater engagement in appearance-based and socially evaluative content [57]. Boys, while less prone to anxiety linked with social comparison, may show higher addictive tendencies related to gaming and video-based platforms. Parental supervision plays a protective role: adolescents with stricter screen-time rules and active parental involvement report lower addiction scores and milder anxiety.

Conversely, weak parental monitoring is associated with more unregulated social-media use and higher emotional distress. Academic stress further amplifies the link between social-media addiction and anxiety, as students turn to platforms for escapism while simultaneously facing pressure to perform well [58]. Late-night social-media use disrupts sleep, exacerbating worry and concentration difficulties. These findings suggest that gender-sensitive, family-involving, and stress-aware strategies are essential for mitigating the negative effects of social-media overuse on adolescent mental health.

5.4 Implications for Adolescent Mental Health

The study has important implications for adolescent mental health, emphasizing the need to integrate digital-wellness education into existing psychological support systems. Schools and counsellors should recognize social-media addiction as a potential marker of underlying anxiety and other emotional difficulties, rather than dismissing it as mere “screen time.” Early identification through routine screening can help distinguish between casual use and addictive patterns that warrant intervention [59]. Digital-literacy programs can teach adolescents to manage social-media use, set time limits, and critically evaluate online content, reducing anxiety-promoting behaviours such as social comparison and fear of missing out.

Families can benefit from guidance on establishing healthy digital boundaries and open communication about online experiences. Mental-health services should address both social-media overuse and anxiety through cognitive-behavioural and mindfulness-based interventions tailored to adolescents [60]. By treating social-media-related behaviours as part of a broader mental-health framework, practitioners can better support the emotional well-being of Indian youth in an increasingly digital world.

5.5 Policy and School-Based Interventions

The findings call for targeted policy and school-based interventions to promote responsible social-media use and protect adolescent mental health. At the policy level, guidelines can be developed for age-appropriate social-media access, including restrictions on late-night usage and recommendations for screen-time limits in educational settings [61]. Schools can implement digital-wellness curricula that combine mental-health education with practical skills such as time management, stress reduction, and cyber-safety. Teacher training programs can equip educators to identify signs of social-media addiction and anxiety, enabling timely referrals to counselling services.

Parent workshops can help families establish digital-use agreements, monitor online activity respectfully, and foster open dialogue about social-media experiences. Peer-support groups and student-led digital-cleanse campaigns can encourage healthier online habits through social modelling [62]. Moreover, integrating anxiety screening into routine school health assessments can facilitate early detection and intervention. These combined efforts can create a supportive ecosystem that reduces the adverse effects of social-media overuse on Indian adolescents and fosters resilient mental-health outcomes.

6. Conclusion

This study concludes that social media–related addictive behaviours are strongly associated with anxiety disorders among Indian school-going adolescents, with higher addiction scores predicting greater anxiety severity even after controlling for demographic and academic

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factors; female adolescents and those with weak parental supervision appear particularly vulnerable, highlighting the role of gender, family environment, and late-night use in shaping mental-health outcomes. To address these risks, schools should integrate digital-wellness and mental-health education into the curriculum, train teachers to identify early signs of problematic social-media use and anxiety, and provide accessible counselling services, while parents are encouraged to set clear screen-time rules, promote offline activities, and maintain open dialogue about online experiences. Future research should adopt longitudinal designs to examine causal pathways, explore platform-specific effects, and evaluate the effectiveness of targeted interventions in diverse Indian settings to further strengthen adolescent mental-health promotion.

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