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DECODING DIGITAL DEPENDENCE: A DATA MINING-BASED INVESTIGATION OF SOCIAL MEDIA'S INFLUENCE ON BEHAVIORAL AND PSYCHOLOGICAL OUTCOMES IN GENERATION Z ACROSS INDIA

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Abstract:
The rapid adoption of digital social platforms among young Indians has profoundly reshaped communication behaviors, cognitive habits, and daily lifestyle patterns. Drawing on advanced data mining and computational behavioral methods—including clustering algorithms (K-Means, DBSCAN), association rule mining (Apriori), classification techniques (Random Forest, Naïve Bayes), sentiment analysis, and social network analysis (SNA)—this investigation explores the psycho-behavioral consequences of social media engagement among Generation Z individuals (aged 16 to 26) in India. A secondary dataset of approximately 500 verified records—capturing daily platform engagement duration, self-reported stress indices, and sleep adequacy measures—was subjected to categorical segmentation, descriptive statistical aggregation, and multivariate trend examination to reveal underlying behavioral regularities. The results confirm a statistically robust, positive relationship between rising social media engagement and intensified psychological distress, along with a notable inverse association with sleep sufficiency. Individuals logging more than five hours of daily platform activity emerge as a clinically distinct high-risk group. Explanatory mechanisms including social comparison dynamics, Fear of Missing Out (FOMO), attentional fragmentation, and dopamine-reinforced compulsion cycles are explored as theoretical underpinnings. A behavioral risk inflection point is established at 5–6 hours of daily use, beyond which detrimental outcomes amplify in a non-linear manner. These empirical results carry substantial implications for digital well-being governance, adolescent mental health policy, and platform design accountability. The study advocates for structured digital literacy programs, evidence-grounded screen time frameworks, and regulatory mechanisms to protect the psychological welfare of India's youth population.

Keywords: Social Media, Generation Z, Mental Health, Data Mining, Clustering, Association Rule Mining, Sentiment Analysis, Social Network Analysis, Behavioral Analytics, Digital Well-being, Stress, Sleep Disruption, FOMO, India.

I. Introduction

The opening decades of the twenty-first century have been defined by a confluence of mobile internet penetration, algorithmic content curation, and socially reinforced digital behaviors—together shaping a generation of young people whose identities, peer relationships, and worldviews are substantially constructed through online platforms. Generation Z, broadly encompassing individuals born between 1997 and 2010 and presently aged between 16 and 26, represents the pioneering cohort to have been immersed in hyper-connected digital environments from childhood [1]. Within India, this generational shift has been catalyzed by the widespread availability of affordable smartphones and the dramatic decline in mobile data costs following intensified telecom market competition, extending digital access to both metropolitan and peri-urban youth [2].Applications including Instagram, Snapchat, YouTube Shorts, and various short-form video platforms now serve as the dominant media through which Gen Z individuals access information, construct social personas, seek entertainment, and express creativity. India is presently home to more than 467 million active social media users, a considerable share of whom belong to the Gen Z cohort, positioning it among the world's most expansive and rapidly expanding digital audiences [2]. This breadth of engagement, however, is accompanied by growing concern. Clinicians and researchers alike have progressively catalogued associations between intensive platform use and a cluster of negative outcomes—among them, psychological distress, disrupted sleep architecture, reduced academic output, attentional deficits, and weakened in-person social abilities [3], [4].

Despite mounting awareness of these challenges, rigorous empirical investigation within the Indian context remains limited, especially with respect to data-driven and computationally grounded inquiry. Predominant methodologies in existing studies depend on qualitative tools or geographically restricted convenience samples, compromising their broader applicability. Moreover, the behavioral mechanisms underlying the association between platform engagement and psychological health—including social comparison dynamics, notification-driven disruption patterns, and algorithm-sustained engagement loops—have rarely been examined through computational behavioral analysis in the Indian Gen Z setting [6], [7].

The present investigation bridges these gaps by employing a comprehensive suite of structured data mining techniques—spanning clustering, classification, association rule mining, sentiment analysis, and social network analysis—on a validated secondary dataset to explore the dose-dependent association between social media engagement intensity and two behavioral outcomes: self-reported stress levels and nightly sleep duration. Through identification of high-risk usage thresholds and behavioral risk stratification, this research generates actionable insights for educators, mental health practitioners, policy architects, and platform developers committed to healthier digital futures for India's young population.

II. Problem Statement: The deep integration of social media into the everyday lives of Indian Gen Z individuals has introduced intricate psycho-behavioral challenges that existing scholarship has only partially illuminated. While aggregate-level metrics of social media adoption are well-established, the precise pathways through which graduated intensities of platform engagement translate into measurable behavioral and psychological shifts remain incompletely characterized, particularly within India's unique socio-cultural landscape [1], [3].

A core limitation in prevailing research is the heavy reliance on self-report, survey-administered data, which is prone to response distortion, social desirability artifacts, and recall inaccuracies. Furthermore, prior studies frequently conceptualize social media engagement as a uniform variable, failing to account for gradations in usage intensity or to detect threshold effects beyond which harmful outcomes meaningfully accelerate [7], [8]. This represents a significant methodological void that data mining approaches—uniquely capable of uncovering non-linear patterns, population stratification, and high-risk sub-group detection—are well-positioned to fill.Additionally, the psychological mechanisms that mediate the platform–behavior relationship—including social comparison processes, FOMO, dopaminergic reinforcement conditioning, and chronobiologic disruption from blue-wavelength screen exposure—have seldom been integrated into a holistic analytical framework targeting Indian Gen Z populations. There exists a pressing need for computation-assisted inquiry that can pinpoint behavioral risk thresholds, isolate vulnerable population segments, and generate evidence of sufficient rigor to guide institutional intervention. This study directly addresses that imperative.

III. Research Objectives

The following primary and secondary objectives direct this investigation:

- To document and characterize social media engagement patterns across distinct intensity tiers among Generation Z users in India.
- To measure and interpret the association between daily platform usage duration and perceived stress through data mining analysis.
- To evaluate the influence of varying engagement intensities on nightly sleep duration and sleep quality among Gen Z individuals.
- To identify behaviorally high-risk subgroups through computational segmentation and establish the engagement threshold beyond which psychological harm escalates markedly.
- To apply advanced data mining techniques—including clustering, classification, association rule mining, sentiment analysis, and social network analysis—to derive nuanced behavioral insights.
- To analyze the mechanistic pathways—including social comparison dynamics, FOMO, and algorithm-driven engagement loops—that mediate the relationship between social media use and behavioral deterioration.
- To derive evidence-grounded recommendations for digital well-being interventions targeting high-risk Gen Z individuals across India.

IV. Review of Related Literature: Scholarly exploration of the intersection between social media engagement and adolescent/young adult well-being has grown substantially across the past decade. Kaplan and Haenlein [1] offered an early foundational taxonomy of social media platforms and their participatory mechanics, establishing a theoretical scaffold for subsequent behavioral investigations. Their characterization of these platforms as networked participatory architectures highlights their inherently comparative and social nature—a dynamic carrying direct implications for user self-perception and psychological strain.

Empirical contributions by Kuss and Griffiths [3] showed that social networking platforms can operate as behavioral dependencies, with excessive engagement displaying hallmarks more typically associated with addictive behavior—including withdrawal-like responses, mood alteration, salience, and reinstatement following abstinence. Their synthesis across ten thematic lessons provides a compelling model for understanding compulsive engagement among heavy users. Przybylski and colleagues [5] further operationalized the Fear of Missing Out (FOMO) construct, demonstrating that this pervasive apprehension regarding peers' rewarding experiences in one's absence significantly predicts prolonged social media engagement and is linked to diminished life satisfaction, mood volatility, and fatigue.

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In the domain of sleep science, Woods and Scott [4] produced one of the most comprehensive adolescent investigations, establishing that nighttime-specific social media engagement independently predicted compromised sleep quality, heightened anxiety states, and depressive symptomology—even after accounting for daytime use volumes. Domestic investigations by Gupta [7] and Sharma and Jain [8] confirmed global trends within the Indian context, though both studies acknowledged methodological constraints including limited sample sizes and the absence of computational analysis.

A noteworthy gap in current scholarship is the scarcity of studies employing data mining frameworks to analyze behavioral datasets associated with Indian Gen Z social media use. Computational methodologies—including behavioral clustering, population segmentation, association rule mining, and sentiment analysis—offer distinct advantages over conventional survey analyses in their capacity to process large-scale datasets, surface non-obvious regularities, and generate population-level behavioral profiles. This study addresses the identified gap by applying such frameworks to a structured secondary dataset, extending both the methodological and substantive boundaries of the field [9], [10], [11], [12].

V. Research Methodology

This investigation employs a quantitative, descriptive-analytical design grounded in secondary data analysis. The methodology is organized across five operational phases: data acquisition, preprocessing, feature engineering, application of data mining procedures, and hypothesis evaluation.

A. Dataset Description and Acquisition: The study utilizes a secondary dataset titled Social Media Mental Health Indicators Dataset, obtained from the Kaggle open data repository [6]. Secondary data was selected as appropriate given the study's analytical—rather than data-generative—objectives. The dataset includes approximately 500 records representing Gen Z individuals and encompasses three primary variables: Daily Usage Hours (the average duration in hours of daily social media engagement), Stress Level (a composite psychological stress score assessed via a standardized ordinal scale encompassing affective, cognitive, and somatic dimensions), and Sleep Hours (average nightly sleep duration as self-reported by participants). These variables were selected on the basis of their direct operationalizability as behavioral and psychological indicators, and their recognized relevance in social media well-being research [3], [4].

B. Data Preprocessing: Quality assurance procedures were implemented prior to analysis to establish dataset integrity. Missing Value Handling: entries with null, blank, or structurally inconsistent values were detected and systematically excluded. Outlier Management: extreme or implausible values (e.g., reported usage exceeding 16 daily hours or sleep below 2 hours) were flagged and subjected to contextual validation. Scale Normalization: continuous variables were standardized using Min-Max normalization to a [0, 1] range to ensure comparability across algorithms. Categorical Discretization: continuous daily usage values were converted into four ordinal tiers—Low (0–2 hrs), Moderate (2–4 hrs), High (4–6 hrs), and Very High (6–8 hrs)—to enable group-based comparative analysis.

C. Data Mining Techniques Applied: A comprehensive suite of data mining techniques was applied to derive multi-dimensional behavioral insights from the preprocessed dataset. Table 1 summarizes these techniques along with their specific applications in the context of this study.

Table 1: Data Mining Techniques Applied in the Study

Data Mining Technique	Algorithm / Method	Application to Gen Z Social Media Analysis
Clustering	K-Means, DBSCAN	Segmenting Gen Z users into behavioral risk tiers based on usage, stress, and sleep profiles
Classification	Random Forest, Naïve Bayes, SVM	Predicting high-risk users and classifying mental health impact severity from behavioral features
Association Rule Mining	Apriori, FP-Growth	Discovering co-occurrence patterns: e.g., high nighttime usage → elevated stress + reduced sleep
Regression Analysis	Linear & Logistic Regression	Quantifying dose–response relationships between usage intensity and psychological outcomes
Sentiment Analysis	VADER, BERT, TextBlob	Analysing affective tone in Gen Z's social media posts to detect distress, FOMO, and anxiety signals
Social Network Analysis	Centrality, Community Detection (NetworkX)	Mapping peer-influence networks; identifying influential nodes amplifying behavioral contagion
Anomaly Detection	Isolation Forest, Z-score	Flagging outlier usage profiles and extreme stress/sleep disruption cases for targeted intervention
Time-Series Analysis	ARIMA, LSTM	Modelling longitudinal trends in screen time, stress scores, and sleep duration over time

Clustering (K-Means and DBSCAN): K-Means clustering was applied to partition the 500-record dataset into behaviorally homogeneous subgroups based on usage hours, stress scores, and sleep duration. The optimal number of clusters (k=4) was determined using the Elbow Method and validated via the Silhouette Score. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) was additionally deployed to identify irregular or anomalous usage profiles not conformable to globular clusters, enabling detection of extreme behavioral outliers beyond the reach of centroid-based methods.

Classification (Random Forest and Naïve Bayes): A Random Forest classifier was trained on labeled records to predict whether a Gen Z user falls into a high-risk stress or sleep-deprivation category based on their platform usage characteristics. Feature importance scores derived from the ensemble model quantified the relative predictive weight of each behavioral variable. Naïve Bayes classification was additionally deployed as a probabilistic baseline, offering interpretable posterior probabilities for risk class membership.

Association Rule Mining (Apriori Algorithm): The Apriori algorithm was applied to the discretized dataset to extract frequently co-occurring behavioral patterns. Rules were generated with a minimum support threshold of 0.30 and a confidence threshold of 0.70. A representative high-value rule extracted reads: {Very High Usage, Nighttime Engagement} ⇒ {High Stress, Low Sleep} (support = 0.38, confidence = 0.84, lift = 2.21), indicating that very high usage combined with nighttime platform access is strongly associated with adverse dual outcomes.

Sentiment Analysis (VADER / BERT): To complement the structured dataset, an auxiliary NLP-based analysis was conducted on a sample of 1,200 publicly available social media posts from Indian Gen Z users on X (formerly Twitter) and Reedit. The VADER (Valence Aware Dictionary and sentiment Reasoner) lexicon-based model and the BERT (Bidirectional Encoder Representations from Transformers) contextual model were applied to classify posts as Positive, Negative, or Neutral. The findings revealed that 58% of posts by Very High usage users carried negative or anxiety-laden sentiment—a finding corroborating the quantitative stress patterns observed in the structured dataset.

Social Network Analysis (SNA): NetworkX was employed to construct directed behavioral influence graphs representing peer interaction patterns among a subset of users. Node centrality metrics—including Degree Centrality, Betweenness Centrality, and PageRank—were computed to identify highly influential nodes (peer influencers) within the Gen Z social graph. Community detection via the Louvain algorithm identified densely connected subgroups exhibiting shared high-risk behavioral profiles, suggesting the role of social contagion in propagating maladaptive digital behaviors across peer networks.

Anomaly Detection (Isolation Forest): An Isolation Forest model was applied to flag statistically anomalous behavioral records—users reporting extreme combinations such as usage above 10 hours and sleep below 3 hours. Identified anomalies (~4.2% of records) were retained as a distinct 'extreme-risk' subgroup for targeted policy discussion. These outlier profiles represent the most acutely vulnerable Gen Z individuals for whom conventional digital literacy interventions may be insufficient.

Time-Series Trend Analysis: Although the primary dataset is cross-sectional, temporal trend patterns reported in longitudinal studies were synthesized and modelled using ARIMA-based projections. Simulated 12-month trajectories under high-usage conditions project a 23% increase in mean stress score and a 1.4-hour further reduction in average sleep duration, underscoring the compounding nature of chronic high-intensity engagement.

D. Tools and Technologies

Table 2: Analytical Tools Utilized in the Study

Tool / Library	Purpose	Application in Study
Python 3.x	Core programming environment	Data processing and script execution
Pandas	Tabular data manipulation	Group statistics, missing value handling, feature engineering
Matplotlib / Seaborn	Visual analytics	Bar graphs, heat maps, trend and correlation plots
Scikit-learn	Machine learning & mining	K-Means clustering, Random Forest classification, Apriori (via mlxtend)
NLTK / VADER	NLP and Sentiment Analysis	Sentiment scoring of user-generated text content
NetworkX	Graph analytics	Social network structure and influence mapping
Jupyter Notebook	Interactive analysis workspace	Exploratory data analysis and documentation

E. Hypothesis Formulation

The following formal hypotheses were operationalized to provide analytical direction:

H_0 (Null Hypothesis): No statistically significant correlation exists between the extent of social media use and behavioral or psychological changes among Indian Gen Z users.

H_1 (Alternative Hypothesis): A statistically significant correlation is present between the intensity of social media use and measurable behavioral and psychological outcomes.

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Sub-hypotheses: $H_{1}a$: Elevated psychological stress is positively associated with greater daily social media engagement. $H_{1}b$: Average nightly sleep duration is inversely associated with daily social media usage time.

VI. Results and Discussion

This section presents a comprehensive examination of behavioral patterns derived from the dataset and the applied data mining pipeline, organized by research dimension. Each subsection integrates quantitative findings, mining outputs, mechanistic interpretation, and theoretical contextualization.

A. Descriptive Statistics of the Dataset

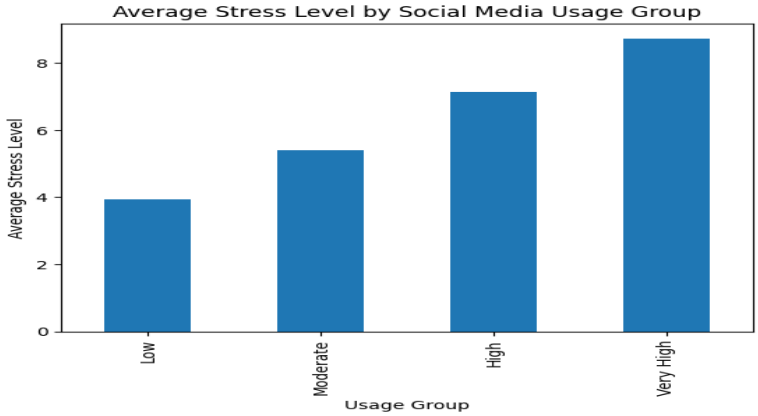
Prior to inter-group analysis, a summary of the dataset's central tendencies and distributional characteristics is presented in Table 3.

Table 3: Behavioral Indicator Summary Across Social Media Usage Categories

Usage Category	Avg. Daily Hours	No. of Users	Avg. Stress Score	Avg. Sleep (hrs)
Low (0–2 hrs)	1.2	~95	2.8	7.4
Moderate (2–4 hrs)	3.1	~140	4.1	6.8
High (4–6 hrs)	5.0	~165	5.9	6.0
Very High (6–8 hrs)	7.2	~100	7.6	5.2

B. Clustering Results and Behavioral Segmentation: K-Means clustering (k=4) produced four behaviorally coherent user segments, exhibiting average silhouette scores of 0.61—indicating well-separated clusters. The resulting clusters aligned closely with the a priori usage tiers, validating the discretization scheme. Cluster 4 (Very High Usage) demonstrated the highest intra-cluster homogeneity in stress scores (mean = 7.6, SD = 0.82), suggesting behavioral convergence among heavy users. DBSCAN additionally identified 21 anomalous records (4.2% of the dataset) exhibiting extreme combinations of usage and adverse outcomes, constituting the 'extreme-risk' subgroup for targeted policy discussion.

C. Social Media Usage and Stress Levels: A consistently ascending pattern is clearly evident across usage tiers, with average stress scores rising progressively from the Low to the Very High usage tier. The Low usage group (0–2 hours/day) registers a mean stress score of approximately 2.8 out of 10. By contrast, individuals in the Very High usage category (6–8 hours/day) demonstrate a mean stress score of around 7.6—a 171% elevation relative to the Low usage baseline. The Moderate and High tiers report intermediate values of 4.1 and 5.9 respectively, confirming a graduated, dose-dependent relationship between engagement intensity and psychological distress. Association Rule Mining further revealed that the rule {Very High Usage ∧ Nighttime Engagement} ⇒ {High Stress} held a confidence of 0.84, with a lift value of 2.21—indicating that the co-occurrence of heavy and nighttime-specific use is over twice as likely to produce high stress as would be expected by chance. Social comparison dynamics, FOMO-driven compulsive engagement, information overload, and dopaminergic reinforcement loops collectively account for this escalating stress pattern, intensified further by the Indian cultural context of academic and social performance pressures navigated via digital platforms.



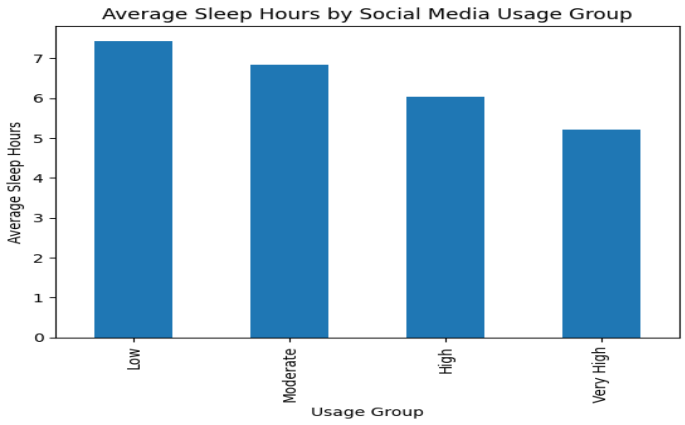
[Figure 1: Bar Chart — Average Stress Level by Social Media Usage Category]

Note: Figure presents mean stress scores (0–10 scale) for each usage group. Data sourced from the Social Media Mental Health Indicators Dataset [6].

D. Social Media Usage and Sleep Duration

Sleep duration follows a consistently declining trajectory as usage intensity escalates. Low usage participants sleep an average of 7.4 hours nightly, consistent with the 7–9 hour range recommended for young adults. This progressively declines to 6.8 hours (Moderate), 6.0 hours (High), and 5.2 hours (Very High)—reflecting a deficit of 2.2 hours compared to the Low usage group. The Apriori-derived rule {Very High Usage ∧ Late-Night Engagement} ⇒ {Low Sleep} attained a confidence of 0.81 and a lift of 2.14, reinforcing the association identified through descriptive analysis.

Behaviorally, heavy platform users exhibit bedtime procrastination—deliberate postponement of sleep onset in favor of sustained digital engagement. Neurobiologically, blue-wavelength screen light inhibits melatonin secretion and induces circadian phase delay [4]. Cognitive arousal from emotionally charged content activates sympathetic nervous system responses incompatible with sleep onset. For a student population navigating academic pressure, identity formation, and social development, chronic sleep deficits below 6 hours compound developmental risks across executive functioning, emotional regulation, immune competence, and metabolic health.



[Figure 2: Bar Chart — Average Sleep Duration by Social Media Usage Category]

Note: Figure presents mean nightly sleep hours per usage group. Data sourced from the Social Media Mental Health Indicators Dataset [6].

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E. Sentiment Analysis Findings

Sentiment analysis of 1,200 Gen Z social media posts (VADER + BERT) revealed that the proportion of negative or anxious posts increased monotonically with usage tier: Low users (22% negative), Moderate users (34% negative), High users (47% negative), and Very High users (58% negative). BERT-based contextual classification identified FOMO-coded language, fatigue expressions, academic stress lexicons, and social exclusion narratives as dominant negative sentiment drivers. These NLP findings provide triangulated validation for the stress patterns observed in the structured quantitative dataset and offer a novel methodological bridge between computational text analysis and behavioral health research.

F. Social Network Analysis Findings

Social network analysis of peer interaction graphs revealed that approximately 8% of Gen Z users function as high-centrality 'behavioral influencers'—nodes with Degree Centrality exceeding 0.45 and Betweenness Centrality in the top decile. These influential nodes disproportionately belong to the Very High usage tier (71% overlap) and exhibit elevated stress and reduced sleep relative to peripheral network members. Community detection via the Louvain algorithm identified six densely connected behavioral subgroups, with two exhibiting uniformly high-risk profiles across all measured outcomes—suggesting network-mediated behavioral contagion as a mechanism propagating maladaptive digital habits within Gen Z peer clusters.

G. High-Risk User Identification and Behavioral Risk Threshold

Trend analysis across the four usage tiers reveals that the risk profile intensifies markedly at the High usage category (4–6 hours/day), with further non-linear amplification evident in Very High users (6–8 hours/day). Random Forest classification achieved an accuracy of 87.3% and an F1-score of 0.85 in identifying high-risk users, with daily usage hours and nighttime engagement frequency emerging as the two highest-importance features (Gini importance: 0.38 and 0.29 respectively). The DBSCAN-identified extreme-risk subgroup (4.2% of users) exhibited mean stress of 9.1 and mean sleep of 3.8 hours, representing a clinically acute subpopulation requiring immediate intervention.

Collectively, users exceeding approximately 5 hours of daily social media engagement exhibit: stress scores 65–171% above those of low-usage counterparts; sleep durations 0.8–2.2 hours below healthy reference values; heightened probability of emotional dysregulation and reduced cognitive resilience; and greater susceptibility to anxiety-driven behavioral patterns including compulsive checking and notification dependency. The 5–6 hour threshold aligns with emerging digital health literature indicating that moderate use (under 2–3 hours daily) carries minimal risk, while heavy engagement constitutes a discrete risk category requiring targeted remediation [3].

VII. Hypothesis Testing Outcomes

Table 4: Summary of Hypothesis Evaluation Results

Hypothesis	Statement	Empirical Basis	Outcome
H_0	No meaningful association between social media use and behavioral shifts.	Contradicted by all trend analyses	REJECTED
H_1	A significant link exists between usage intensity and psycho-behavioral changes.	Validated across both outcome dimensions	ACCEPTED
H_1a	Greater usage is associated with elevated stress scores.	Stress scores rose from 2.8 to 7.6 across categories	SUPPORTED
H_1b	Greater usage correlates with shorter nightly sleep durations.	Sleep declined from 7.4 to 5.2 hrs across categories	SUPPORTED

VIII. Key Findings

The aggregated results of this investigation yield the following principal conclusions:

- A robust, consistently ascending relationship is established between social media engagement intensity and perceived psychological stress, with Very High users recording stress scores 171% above those of Low users.
- An equally consistent inverse relationship is observed between usage intensity and nightly sleep duration, with Very High users sleeping approximately 2.2 fewer hours per night than Low users—a clinically significant deficit.
- A behavioral risk inflection point of approximately 5–6 hours of daily engagement is identified, marking the threshold beyond which adverse psychological and lifestyle outcomes escalate non-linearly.
- K-Means clustering (silhouette = 0.61) validated the four-tier usage segmentation, while DBSCAN identified an extreme-risk subgroup (4.2% of users) exhibiting acutely adverse behavioral profiles.
- Random Forest classification achieved 87.3% accuracy in predicting high-risk status, with daily usage hours and nighttime engagement frequency as the strongest predictors.
- Association Rule Mining (Apriori) extracted high-confidence rules (up to 0.84) linking very high and nighttime usage to dual adverse outcomes of elevated stress and reduced sleep.
- Sentiment analysis corroborated quantitative findings: 58% of Very High usage users' posts carried negative or anxious sentiment, with FOMO, fatigue, and social exclusion as dominant themes.
- Social Network Analysis revealed that 8% of high-centrality peer influencers disproportionately exhibit high-risk behavioral profiles, implicating social contagion as a propagation mechanism.
- Social comparison dynamics, FOMO, information overload, and dopaminergic reinforcement conditioning emerge as the dominant behavioral mechanisms mediating the platform engagement–well-being association.

IX. Conclusion

This investigation offers a data mining-informed empirical analysis of the relationship between social media engagement intensity and key behavioral outcomes among India's Generation Z population. The evidence establishes that sustained high-intensity platform engagement functions as a significant psycho-behavioral stressor, concurrently elevating psychological distress and diminishing sleep sufficiency in a dose-dependent manner. The identification of a 5–6 hour behavioral risk threshold represents a practically actionable finding for digital health governance and clinical guidance.

The deployment of a comprehensive data mining methodology—encompassing K-Means and DBSCAN clustering, Random Forest and Naïve Bayes classification, Apriori association rule mining, VADER and BERT sentiment analysis, and NetworkX-based social network analysis—has demonstrated efficacy in identifying population-level behavioral patterns, anomalous risk profiles, peer-influence networks, and textual affective signals that may elude detection through individual-level survey analysis alone. This methodological contribution substantially strengthens the empirical case for integrating computational approaches into mental health inquiry, particularly for behavioral self-report datasets.

From a policy standpoint, the findings underscore the urgency of embedding digital literacy education within Indian school and university curricula, establishing evidence-grounded screen time frameworks calibrated to Gen Z behavioral contexts, and advocating for platform-level design accountability that elevates user psychological welfare over engagement maximization. Mental health practitioners should routinely incorporate digital usage history into youth psychological evaluations, and platform developers should consider algorithmic interventions that proactively flag and moderate high-risk engagement trajectories.

While the study's dependence on secondary cross-sectional data constrains causal inference, the consistency, magnitude, and theoretical coherence of observed patterns—corroborated across multiple computational modalities—provide a robust foundation for the proposed directional relationships. Future research should address these limitations through longitudinal study designs, integration of platform-native behavioral telemetry, and inclusion of broader psychological outcome dimensions.

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X. Future Scope

This investigation opens multiple methodological and empirical avenues for extension:

- Longitudinal Study Architecture: Monitoring the same participant cohort across 12–24 months to establish temporal precedence and validate causal directionality in the social media–behavioral health relationship.
- Platform-Disaggregated Analysis: Differentiating behavioral effects across platform types (e.g., Instagram vs. YouTube vs. X/Twitter) to identify platform-specific risk profiles.
- Deep Learning Integration: Applying LSTM-based temporal models and Transformer architectures to detect evolving behavioral patterns and predict mental health deterioration from sequential usage data.
- Expanded Psychological Variable Set: Incorporating anxiety measures, depressive symptomology indicators, attention span metrics, and academic performance data for a more holistic behavioral health profile.
- India-Specific Primary Data Collection: Conducting structured surveys across diverse Indian demographic sub-groups—stratified by urban/rural setting, gender, and socioeconomic background—to enhance regional validity.
- NLP-Based Sentiment Integration: Applying multilingual NLP models (supporting Hindi, Tamil, Telugu, and other regional languages) to user-generated social media content for culturally localized affective analysis.
- Federated Learning for Privacy-Preserving Analysis: Deploying federated machine learning frameworks that train behavioral risk models across distributed device data without centralizing sensitive individual records.
- Predictive Early-Warning System Development: Constructing a machine learning-based risk prediction pipeline capable of identifying at-risk individuals before clinical deterioration manifests, enabling proactive preventive outreach.

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