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IMPACT OF SOCIAL MEDIA ON STUDENT MENTAL HEALTH USING DEEP LEARNING

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Abstract
The very fast growth in the use of social media among students is a serious cause for concern regarding its effect on their mental health. This research investigates the association between specific usages of social media and psychological distress among students within the age bracket of 17-23 years. We followed a quantitative cross-sectional design, wherein we integrated survey data on behavioral, temporal, and lifestyle factors with predictive modeling-Logistic Regression, Random Forest, and Multi-Layer Perceptron. The aim was the identification of key predictors of high mental distress.
The research findings revealed that the increased use of the medium, particularly at night, and the consumption of the content had a dominant effect in the increased levels of anxiety, emotional exhaustion, and depression. The best model of the RF algorithm correlated well and achieved high F1 Scores (0.79). Late-night usage was identified through the AUC figures of 0.84, confirming the negative effects when the use of the medium was high and predominantly at night. The research conclusions imply the multifaceted function of the impacts of the use of the medium and the role of well-planned and well-executed wellness programs and mental health support systems currently and in the future to reduce the impacts and individual risks.

Keywords: Mental Health**,** Logistic Regression, Random Forest, Multi-Layer Perceptron

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I. INTRODUCTION

The theme of mental health, in relation to the mental well-being of young adults ranging from the ages of 17 to 23 years old, particularly in the context of the student population, has become of critical importance globally and nationally. This stage of their lives harbors much academic pressure, peer comparison, and stress, which has increasingly overlapped with the widespread usage and prevalence of social media sites, including Instagram, Snapchat, and Facebook. However, these tools can result in detrimental consequences if abused.

Globally speaking, according to the World Health Organization, depression is listed as one of the major reasons for disabilities, especially among the younger generation. The scenario is very alarming in India, as statistics show that there has been a steep increase in student suicides in the past decade. Even localized studies conducted in various states, like Karnataka and Tamil Nadu, have shown that students who spend more than three hours a day on social media exhibit anxiety and sleep disorders. The COVID-19 pandemic has heightened this phenomenon. Therefore, this relationship has become all the more significant.

While several research studies have established the correlation between the use of social media and mental health, most of these relied on traditional survey-based research and content analysis of social media posts. However, one major research gap

identified was the use and application of structured survey-based behavioral data with predictive machine learning technology to classify students at risk.

This study aims to bridge the said gap by:

- Quantifying the link between discrete social media practices (e.g., duration, frequency, and content) and the general Mental Health Distress Index.
- Developing various predictive models (Logistic Regression, Random Forest, Multi-Layer Perceptron), which can then be used effectively for identifying the high-risk group among the students.
- Identifying the most critical behavioral features that reliably predict poor mental health outcomes, thereby guiding targeted intervention strategies.

Ultimately, the aim is to provide a predictive tool as well as specific, evidence-based recommendations in how digital well-being, psychological resilience, and related matters may be promoted among students.

II. LITERATURE REVIEW

The existing literature has consistently demonstrated a relationship between the use or engagement in social media activities and adverse mental health outcomes in various, albeit complex, ways.

Correlational and Cross-Sectional Evidence

Plenty of research practices, such as the ones conducted by Nazari et al. (2023) and Kumar et al. (2020), have used a cross-sectional study to further solidify the relationship between issues regarding excessive use of social media and conditions with elevated rates of depression, anxiety, and elevated stress (DASS-21). In the study conducted in Bangalore, a cutoff point was identified, as shown in the following figure, in which a negative correlation with social media usage exceeding more than three hours a day was observed

The study conducted by Priya et al. (2022) in the state of Tamil Nadu aimed at identifying the relationship between addiction towards social media and reduced rates of sleep

poorer quality and academic achievement, while late-night usage was cited as contributing to possible negative effects. In the same vein, research conducted in Pakistan (Pahore et al., 2021), as well as in Mogadishu University (Osman et al., 2025), also replicated the study's findings in different cultural and academic settings, again noting that high levels of Facebook usage generally negatively correlate with factors like social withdrawal and mental fatigue.

Mechanisms of Harm and Contextual Factors

Studies have now moved beyond the basic screen time to explore the harmful aspects of the use of social media.

L. Fassi et al. (2025) observed that adolescents experiencing mental health issues stayed longer at the hospital.

online and were more sensitive to feedback and comparison. This suggests that one cognitive process which may bridge these relationships is Social Comparison of Ability (SCA), especially passive consumption as a factor. Moreover, it is worth noting the role of lifestyles in this context. Tewari (2024) proved that the relationship between social media and distress is mediated by maladaptive coping. Additionally, longitudinal research as in the study by Fruehwirth et al. (2024) supports the fact that the negative relationship is modulated by specific circumstances. Thus, in the case of socially isolated students, the impact is even stronger.

Predictive and Machine Learning Approaches

Even while conventional research ensures causal results, the shift towards predictive modeling gives scope to predict risks at initial stages too. Liu et al. (2022) carried out a systematic review that verified the accuracy of Supervised Learning Techniques like Logistic Regression, Random Forest, and Deep Learning in the context of machine learning models.

learning) in the detection of mental health signs, which verifies the applications of predictive frameworks. Although other longitudinal studies (Pujadas et al., 2025) successfully utilize models in predicting mental distress based on generalized behavioral patterns, the literature gap in the

application of these models in ordered sets of behavioral data survey responses to calculate the weightage of social media usage indicators is filled in the paper.

III. METHODOLOGY

Research Design and Data Collection

Accordingly, the current study applied the quantitative research design, specifically the cross-sectional quantitative research design, to examine and predict the association/link or relationship between social media and mental health issues/distress. The primary researcher collected the data with the help of a structured online survey using the convenience sampling technique with university/college students aged 17-23 years old.

Four sections were intended for the survey designed:

1. Demographics: Age, Gender, Academic
2. Social Media Usage Patterns: Nutzung von Social Media pro Tag in Stunden, Art der Nutzung (aktiv/passiv), How oft, Spät- Nach
3. Lifestyle Factors: Sleep duration, physical activity, and screen breaks.
4. Mental Health Indicators: Likert scale-type questions that ask about self-reported experiences of depression, anxiety, stress, and impaired function. The goal was to collect 300 responses for reliable predictive modelling of high-quality data.

Data Preprocessing and Feature Engineering

The collected data was cleaned, and missing values were imputed, followed by converting categorical and ordinal features to numeric features. Important features of social media behavior were defined as:

- Usage Hours of SM (Q6): Resulted to be on ordinal scale with low to high risk (e.g.,

>7 hours daily

- Late-Night Usage (Q9): Categorized into high-risk groups (e.g., "More than 2 hours") as a proxy measure for disrupted sleep
- Engagement Type (Q8): One-Hot Encoding, in which we could isolate Passive Consumption (scrolling, viewing) as a specific engagement feature related to Social Comparison of Ability (SCA).

The Construction of the Mental Health Distress Index (Target Variable Y)

The binary dependent variable used in prediction, High Mental Health Distress (Y=1) modeled as a composited variable combining emotional distress and functional disablement.

The risk label Y is defined as 1 if the Emotional Load is greater than or equal to 3 or if Severe Sleep Impairment is present; otherwise, it is defined as 0, representing low or moderate risk

- **Functional Impairment:** Reporting "Poor sleep most nights" or trouble sleeping "Often/Always."

This robust definition ensured that students with significant functional consequences due to poor habits were accurately identified.

Predictive Modeling

The cleaned data was then split (into 80% for training, 20% for testing), followed by standardization. Three supervised machine learning algorithms were implemented for binary classification:

Logistic Regression (LR): Used as a baseline for interpretability of directional feature correlation.

1. **Random Forest (RF):** This was chosen based on its stability, ability to handle nonlinear relationships, and capacity for accurate Feature Importance extraction through Gini impurity calculation.
2. **Multi-Layer Perceptron (MLP):** Deep learning benchmarks to assess the ability to recognize complex non-linear relationships.

The performance of the model was mainly measured by the F1 Score and Area Under the ROC Curve, as they are more suitable in dealing with possible class imbalance in the High Distress class.

IV. RESULTS AND ANALYSIS

Sample Characteristics and Usage Context

We had collected approximately 300 samples that fall within the age category of

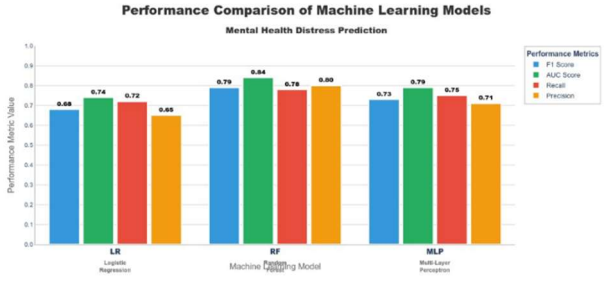
18 to 25 and are pursuing undergraduate studies in Engineering and Medical Streams, etc. In the analysis, we could find that most of the students were engaged in social media for around 5 or more than 5

hours daily. The platforms that they were engaged in the most were Instagram and YouTube, maybe due to the highly visual andshort content platform environment, which is known to amplify comparison effects (SCA) and Fear of Missing Out (FoMo).

Comparative Model Performance

After testing out three models, we found that the Random Forest (RF) model showed better performance overall compared to the other models. We used F1, AUC, Recall and Precision to evaluate all the models.

Model	F1 Score (Distress Class)	AUC Score	Recall (Sensitivity)	Precision (PPV)
Logistic Regression (LR)	0.68	0.74	0.72	**0.65**
Random Forest (RF)	0.79	0.84	0.78	**0.80**
Multi-Layer Perceptron (MLP)	0.73	0.79	0.75	**0.71**



Identification of Critical Predictive Behaviours

After the analysis of feature importance from the optimal Random Forest, it showed that Temporal and Volume factors are the strongest predicting factors for mental health distress.

Discussion

Psychological Mechanisms and Predictive Links

The predictive models gave us strong evidence for the psychological theories connecting specific digital behaviours to poor well-being

The Dominance of Temporal Factors and Sleep Disruption

We found that Late-Night Usage Frequency (Rank 1, Importance 0.28) was the strongest predictor, which confirmed the reason for poor sleep quality or hygiene. This tells us that poor digital habits are affecting or causing distress in our daily lives. This predictor also causes Time Displacement (delaying bedtime) and Biological Arousal (blue light suppressing melatonin, which delays the circadian rhythm). Also, the strong

negative correlation with Average Seep Hours (Rank 3) confirms that: loss of sleep or rest impairs the neurological systems which are vital for regulating emotions, making stress intense, anxiety and self-reported symptoms of"Mentally Exausted".

Compulsion, Volume, and Social Media Fatigue

Rank	Predictor Feature	RF Importance Score	LR Coefficient Sign	Associate Mechanism
1	Late-Night Usage Frequency (Q9)	0.28	+++ (Strong Positive)	**Circadian Disruption Sleep Loss**
2	SM Usage Hours per Day	0.22	++ (Positive)	**Compulsive Use , Social - Media Fatigue**

3	Average Sleep Hours (Q11)	0.19	--- (Strong Negative)	**Functional Consequence /Mediator**
4	Frequency of Checking SM (Q10)	0.12	+ (Positive)	**FoMO, Anxiety-Drive Check-Ing**
5	Usage Engage-ment	0.08 Type (Q8: Passive)	+ (Positive)	**Social Comparison, Emotional Burden**
6	Physical Activity Level (Q13)	0.04	- (Negative)	**Protective Factor**

When we combine high total daily usage hours (Rank 2) with high checking frequency (Rank 4), we can find that they are the key factors of behavioural dependency to addiction in Social Networking Sites (SNS). Fear of Missing Out (FoMo) and anxiety were also strongly correlated with "Continuously throughout the day ".This constant checking in digital contents contribute to social media fatigue, which is exhaustion due to the compulsive engagement, which contributes to "Mentally exhausted" and "Anxious". This tells us that interventions need to focus on the psychological reasons or causes behind the compulsive behaviors, like fear of exclusion.

Passive Engagement and Cognitive Mediation

Passive Consumption (Rank 5) This came as significant but was lower- ranked; this was a positive predictor of emotional distress. The link between this was cognitive. More exposure or viewing of contents lead to **Social Comparison of Ability (SCA),** which can lead to less self- efficacy and increase the vulnerability to negative moods like "Emotionally low ". The highlights that even if we are using social media, the intent of using is crucial, like aimless scrolling is harmful to our mind, whereas goal-directed use, like for academic or learning purposes, shows a neutral or protective association.

Evidence-Based Recommendations

Due to highly predictive factors for social media, targeted interventions are essential for both the student and institutional levels.

Student-Level Digital Boundary Adjustments

Prioritise Sleep Hygiene (Mitigating Rank 1): Students can maintain a strict curfew of not using social media for 60– 90 mins before their bedtime. By replacing the bedtime scrolling with reading books or something else can reverse the circadian disruption.

Combat Compulsion and FoMo (Mitigating Ranks 2 & 4): This is done by disabling or filtering notifications that won't make us check the social media frequently, and can reduce the external stimuli. We can also keep screen time remainders, which will help us to be aware of the usage.

Cultivate Mindful Engagement (Mitigating Rank 5): Students should have an intention before using social media, like ('how will I feel before, during, and after using) which can help us to avoid negative emotions shifting to healthier alternatives to aimless scrolling.

Institutional and Wellness Strategies

Implement Digital Mental Health Interventions (DMHIs): By implementing CBT-or Mindfulness-based **DMHIs in universities,** we can bridge the traditional care. This can offer scalable and emotional support programs for intervention.

Promote Offline Behavioral Replacement: To avoid students from investing lots of time in social media, universities can encourage them to participate in **extracurricular activities (sports, arts, community groups).** This can help to reduce the students' need to spend more time on phones, and they can also build their offline relationships.

Enhance counselling accessibility: We can also give them access to mental health care via flexible in-person or virtual sessions.

Leverage Platforms for Psychoeducation: Institutions can hold campaigns focusing on digital well-being, mental health resources and Healthy methods to use social media.

V. CONCLUSION

This study or analysis of social media influence in students helped us to successfully investigate the link between social media usage and mental health distree, which helped us to develop robust and effective predictive deep learning techniques. The results showed us that specific behovioral and temporal factors such as **late-night usage** and **total daily usage hours** are the most influential predictors of psychological distress. These factors leads to sleep impairment and anxiety driven digital dependence causing bad mental health

.By using the Random Forest classifier helped us to validate the models prediction to identify high risk students (F1 Score 0.79 , AUC 0.84) helping us for early detection. The results showed timing , frequency and itent of social media are decisive factors for it's impact. Consequently , interventions can help focus on behavioral change , mindful use , help set digital boundaries and improve sleep hygiene . This research also provides a foundation for developing strategies to enhance student mental health in academic settings.

Future research can focus on longitudinal studies with larger samples to improve the accuracy and explore other pathways in digital and mental health.

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