Understanding Social Media Addiction in the Digital Society through Sleep Deprivation, Conflict, and Emotional Health

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ABSTRACT

In the context of an increasingly digitized society, social media addiction among students has become a pressing concern with implications for psychological well-being, sleep behavior, and interpersonal relationships. This study aims to investigate the behavioral and emotional predictors of social media addiction using a dataset comprising 705 student respondents from various academic levels and countries. The research focuses on four core variables: average daily social media usage, sleep duration per night, self-reported mental health scores, and the frequency of conflicts caused by social media use. Descriptive statistics reveal that social media addiction scores are heavily skewed toward the upper end of the scale, with 209 students (29.6%) scoring 7 and 144 students (20.4%) scoring 8 on a 0–9 scale. Conflict is also prevalent, with 261 students (37.0%) reporting three conflicts and 204 students (28.9%) reporting two conflicts related to social media use. Correlation analysis shows strong relationships between addiction score and the examined variables, with the highest correlation observed with mental health score ($r = -0.95$), followed by conflict frequency ($r = 0.93$), average daily usage ($r = 0.83$), and sleep hours ($r = -0.76$). Three regression models Linear Regression, Random Forest Regressor, and XGBoost Regressor, were applied to predict addiction scores. XGBoost achieved the best performance, with an R^2 score of 0.992 and MSE of 0.026, followed by Random Forest ($R^2 = 0.991$, MSE = 0.029) and Linear Regression ($R^2 = 0.950$, MSE = 0.126). These findings confirm that social media addiction is strongly associated with behavioral intensity, emotional vulnerability, and social conflict. The study contributes to a deeper understanding of digital dependency and underscores the importance of holistic interventions that target not only digital behavior but also psychological and relational well-being in the digital age.

Keywords Social Media Addiction, Digital Society, Sleep Deprivation, Conflict, Mental Health, Machine Learning, Students

Submitted 5 October 2025
Accepted 15 November 2025
Published 1 December 2025

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Additional Information and Declarations can be found on page 325

DOI: 10.63913/jds.v1i4.145

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Introduction

The rise of social media as a dominant mode of communication and self-expression has fundamentally reshaped human behavior, particularly among younger populations [1]. In the context of the digital society—where interactions, identities, and even daily routines are increasingly mediated by algorithms and online platforms—social media has emerged as both an enabler of connection and a source of psychological stress [2]. While these platforms facilitate information sharing, entertainment, and social networking, their design often relies on persuasive technologies such as infinite scrolling, personalized feeds, and instant feedback mechanisms, which can lead to compulsive usage patterns. This phenomenon is widely referred to as social media addiction, characterized by excessive, uncontrollable engagement with social media that disrupts personal, academic, or social functioning [3]. Among university and high school students, the prevalence of social media addiction is notably high.

Students are typically early adopters of digital platforms and are continuously immersed in academic, peer, and leisure activities that rely on mobile connectivity [4]. However, this demographic is also developmentally vulnerable to dopamine-driven reward cycles, peer validation pressure, and emotional dysregulation—factors that make them susceptible to the addictive nature of social media. The consequences are far-reaching: studies have shown correlations between social media overuse and sleep deprivation, mental health deterioration, and interpersonal conflict, particularly as students attempt to balance their academic responsibilities with their digital lives [5].

Despite the growing body of research on digital well-being, existing studies tend to examine these factors in isolation or rely on traditional statistical techniques that may not capture complex interactions between behavioral, emotional, and social variables. There is a clear need for more integrated, data-driven approaches that can model these relationships holistically and offer predictive insights into which students are most at risk of developing problematic patterns of media consumption. In response to this gap, the present study investigates the predictors of social media addiction among students using a dataset of 705 observations. The analysis focuses on four key variables that are frequently cited in the literature as significant correlates of digital overuse: (1) average daily usage hours, (2) sleep duration per night, (3) self-reported mental health score, and (4) number of social media-related interpersonal conflicts. By applying machine learning techniques—specifically Linear Regression, Random Forest Regressor, and XGBoost Regressor—this research aims to quantify the extent to which these factors can accurately predict addiction scores and to evaluate which predictors carry the most influence.

This study not only contributes empirical evidence to the field of digital behavior analysis but also demonstrates the practical utility of computational methods in modeling complex psychological phenomena. The findings are expected to inform digital literacy programs, mental health initiatives, and educational policies aimed at reducing digital dependency and promoting healthier relationships with technology in student populations.

Literature Review

The proliferation of social media platforms in the digital society has generated a surge of academic interest in understanding the psychological, behavioral, and social consequences of excessive online engagement. Social media addiction, in particular, has been conceptualized as a behavioral addiction that mirrors traditional substance addictions in its core symptoms—salience, mood modification, tolerance, withdrawal, conflict, and relapse, as proposed by Griffiths [6]. Students are among the most affected populations, as they are simultaneously frequent users of social media and highly susceptible to the emotional and cognitive effects of continuous online interaction. Numerous studies have identified average daily social media usage as a primary predictor of digital addiction. Kuss and Griffiths [7] and Andreassen et al found that individuals who use social networking sites for more than three to four hours daily are significantly more likely to exhibit addictive behaviors, including decreased academic focus and impaired offline relationships. Furthermore, Balakrishnan and Griffiths [9] emphasized that frequent platform switching—moving between Instagram, Facebook, TikTok, and messaging apps—also intensifies compulsive usage, creating a habitual engagement loop that students find difficult to break.

Sleep deprivation has emerged as another critical factor. Levenson et al [10] and Carter et al [11] established that excessive social media use, particularly at night, is associated with disrupted circadian rhythms, shortened sleep duration, and poor sleep quality. Similarly, Lemola et al reported that nighttime exposure to blue light from screens impairs melatonin production, which, in turn, contributes to insomnia and next-day fatigue—factors that increase the risk of digital overuse. From a psychological perspective, multiple studies point to the bidirectional relationship between mental health and social media use. Shensa et al [13], Twenge and Campbell [14], and Lin et al [15] found strong associations between excessive usage and symptoms of anxiety, depression, and low self-esteem, especially among adolescents and young adults. Valkenburg et al suggested that emotionally vulnerable individuals may rely on social media for mood regulation and social reassurance, which paradoxically reinforces their dependence on these platforms. The phenomenon of "emotional compensation" via social media was further examined by Andreassen [17], who concluded that negative affect often predicts more intensive usage patterns.

Equally important is the role of interpersonal conflict. Lee and Kim [18] showed that digital conflict—arising from misunderstandings, surveillance, or jealousy in social interactions—can heighten social anxiety and reinforce compulsive checking behaviors. Similarly, Elhai et al [19] linked problematic smartphone use to Fear Of Missing Out (FOMO), interpersonal tension, and a heightened need for social reassurance. Marengo et al extended this line of inquiry by demonstrating that higher levels of digital conflict are significantly associated with lower well-being and increased social withdrawal among university students. In recent years, scholars have turned to machine learning methods to model and predict social media addiction more accurately. Zhao et al [21] applied Random Forest and logistic regression to behavioral data and found that ensemble models significantly outperformed traditional regression in identifying addiction risk. Similarly, Islam et al [22] demonstrated the effectiveness of gradient boosting and decision tree classifiers in predicting social media overuse when emotional and usage-based features were combined. These computational approaches allow researchers to capture complex, non-linear interactions that are often difficult to detect using conventional statistical tools.

Despite these advances, there remains a lack of integrated research that simultaneously considers behavioral intensity (e.g., usage time), psychological health (e.g., mental well-being), physiological behavior (e.g., sleep duration), and social strain (e.g., digital conflict) as joint predictors of addiction risk. Therefore, this study seeks to fill that gap by applying Linear Regression, Random Forest, and XGBoost Regressor algorithms to model social media addiction using a dataset of 705 students. By doing so, it contributes not only to the theoretical understanding of digital dependency but also to the practical development of predictive tools for early identification and targeted intervention.

Methods

This study employs a supervised machine learning approach to model and predict social media addiction among students using behavioral and psychological indicators. The methodology involves five primary stages: data preparation, feature selection, preprocessing, model training, and performance evaluation, as shown in Figure . The dataset consists of 705 observations collected via structured questionnaires, containing quantitative measures of social media behavior, emotional well-being, and interpersonal dynamics. The dependent variable, Addicted_Score, is a continuous scale ranging from 0 to 9, indicating the self-reported severity of social media addiction.

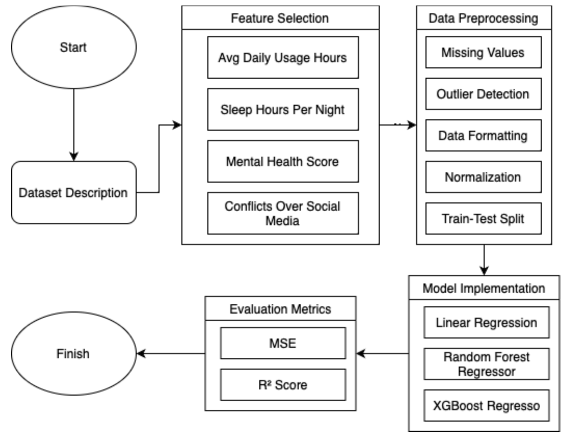

Figure 1 Research Method Flowchart

Four independent variables were selected based on theoretical significance and empirical support in prior studies: (1) Avg_Daily_Usage_Hours, the average number of hours a student spends on social media daily; (2) Sleep_Hours_Per_Night, the average duration of sleep per night; (3) Mental_Health_Score, a self-assessment of emotional well-being where higher scores reflect better mental states; and (4) Conflicts_Over_Social_Media, the number of social-related tensions or disputes triggered by social media use. These features were chosen to represent behavioral, psychological, and social factors relevant to digital dependency.

In the preprocessing phase, the dataset was examined for missing values, of which none were found. Outliers were detected using boxplot visualization and z-score calculations. Observations with implausible values—such as daily usage exceeding 18 hours or sleep under 2 hours—were capped or excluded. All variables were confirmed to be numerical. Normalization was tested using Z-score standardization for the Linear Regression model, but was omitted as it yielded no improvement, and was unnecessary for tree-based models. The cleaned data was partitioned into a training set (80%) and a testing set (20%) using a random seed (42) for reproducibility.

Three regression models were implemented: Linear Regression, Random Forest Regressor, and XGBoost Regressor. Linear Regression served as a baseline model to evaluate linear relationships. Random Forest Regressor, an ensemble learning method, builds multiple decision trees to reduce variance and improve prediction accuracy. XGBoost Regressor utilizes gradient boosting to iteratively minimize residual errors and incorporates regularization to prevent overfitting. Each model was trained on the training data and tested on the holdout set.

To evaluate the models, two standard regression metrics were used: Mean Squared Error (MSE) and the Coefficient of Determination (R^2 Score). The MSE is calculated as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (1)$$

y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the total number of observations. MSE captures the average squared difference between predicted and actual values, serving as a measure of model error [23].

The R² Score is calculated using the formula:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (2)$$

$\bar{y}$ is the mean of the observed values. This metric indicates the proportion of variance in the dependent variable explained by the model. An R² value closer to 1 suggests a better fit between the model and the observed data [24].

Together, these evaluation metrics enabled a comprehensive comparison of the models' predictive capabilities and facilitated the selection of the most effective algorithm for identifying at-risk students based on their digital behaviors and emotional well-being.

Result

This study aims to examine the behavioral and psychological predictors of social media addiction among students by implementing three supervised regression models—Linear Regression, Random Forest Regressor, and XGBoost Regressor—using a dataset comprising 705 individual observations. The analysis focuses on four key independent variables that are theoretically and empirically linked to digital dependency: (1) the average number of hours students spend on social media per day, (2) their average nightly sleep duration, (3) self-reported mental health scores, and (4) the frequency of interpersonal conflicts caused by or related to social media usage. These variables were selected to capture both the behavioral patterns (usage and conflict) and psychological outcomes (sleep and mental health) that may underlie problematic engagement with digital platforms. To explore these relationships, the data were first subjected to descriptive statistical analysis to understand general patterns and distributions. Subsequently, correlation analysis was used to examine the strength and direction of relationships between the independent variables and the addiction scores. Finally, predictive modeling was conducted using the three regression algorithms to evaluate how well these factors explain the variance in students' social media addiction scores and to identify which predictors carry the most influence.

The results from the descriptive analysis suggest that a significant proportion of students exhibit moderate to high levels of addiction to social media platforms. The distribution of addiction scores is presented in table 1, while the same data is visually illustrated in Figure 2 to facilitate intuitive comparison. The data show a clear concentration of students at higher addiction levels, with the most frequent scores being 7 (reported by 209 students) and 8 (reported by 144 students). These scores correspond to the upper end of the 0–9 scale, indicating widespread tendencies toward excessive or habitual social media use. In contrast, very few students reported minimal levels of addiction, with only 1 student at score 2 and 16 students at score 3, suggesting that low-level engagement is relatively rare among the sample population.

Table 1 Addicted Score Distribution

Addicted Score	Number of Students
2	1
3	16
4	83
5	136
6	61
7	209
8	144
9	55

As presented in table 1, the distribution of social media addiction scores among students provides a comprehensive numerical overview of the extent of digital engagement within the sample. The data reveal that the majority of students cluster around higher addiction scores, with the most frequently reported values being score 7 (209 students) and score 8 (144 students). This pattern suggests a strong tendency toward habitual or potentially compulsive use of social media platforms among a significant portion of the student population. In contrast, low addiction scores, such as 2 and 3, were reported by only a very small minority, indicating that minimal usage patterns are uncommon.

To enhance the interpretability and accessibility of this distribution, the same information is depicted graphically in figure 2 using a bar chart. This visual representation facilitates quicker comparative analysis across score levels, allowing readers to immediately grasp the concentration of high-frequency scores. The height of the bars corresponding to scores 7 and 8 dominates the chart, reinforcing the notion that social media usage among students tends to fall on the higher end of the addiction scale. Such visual evidence further supports the argument that excessive social media use is not only prevalent but also potentially systemic in this demographic.

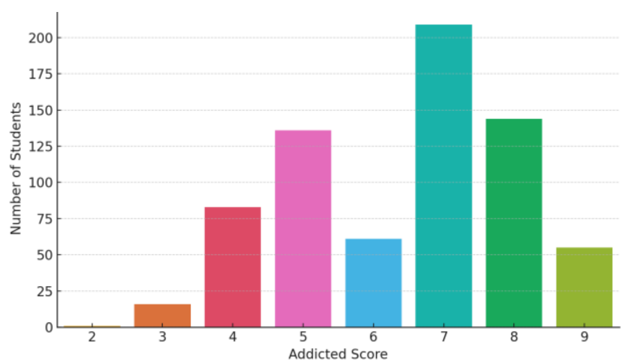

Figure 2 Distribution of Social Media Addiction Scores

Figure 2 presents a bar chart that illustrates the frequency distribution of students' self-reported social media addiction scores, which range from 2 to 9. The data visualization confirms the tabular findings, with score 7 emerging as the most commonly reported level of addiction, followed by score 8. This pattern underscores a significant clustering of students within the higher end of the addiction scale, suggesting a widespread prevalence of habitual or potentially problematic social media use. The visual format of the figure allows for an immediate and intuitive understanding of this trend, highlighting the disproportionate concentration of high-frequency scores compared to the relatively sparse distribution of lower addiction levels.

In addition to high usage patterns, social conflicts arising from social media interactions were also prominently reported among students. As detailed in table 2, a considerable number of respondents experienced multiple conflicts attributable to their social media activities. Specifically, 261 students reported having experienced three conflicts, while 204 students indicated two conflicts, making these the most frequent categories. In stark contrast, only 4 students reported having no conflicts, which suggests that social media is a common source of interpersonal tension within this population. These findings reflect the broader social implications of digital dependency, where excessive or emotionally charged online interactions may translate into real-world relational strain and conflict among peers.

Table 2 Conflict Distribution

Number of Conflicts	Number of Students
0	4
1	47
2	204
3	261
4	174
5	15

While table 2 provides a detailed numerical summary of the frequency of social media-related conflicts reported by students, figure 3 complements and reinforces these findings through a visual format that enhances interpretability. The bar chart clearly illustrates that the highest concentrations occur at 2 and 3 reported conflicts, reflecting a significant proportion of students who experience recurring interpersonal tension linked to their social media usage. This visual representation not only confirms the tabular data but also provides an intuitive understanding of how conflict levels are distributed across the sample.

By highlighting the dominant peaks at 2 and 3 conflicts, figure 3 makes it immediately apparent that social friction in digital environments is not an isolated issue, but rather a common experience among students. The visual clarity of this chart underscores the prevalence and normalization of social strain within digital communication contexts. When viewed alongside table 2, the figure accentuates the social cost of digital dependency, suggesting that frequent conflicts may be an emerging characteristic of student interaction in digitally saturated environments.

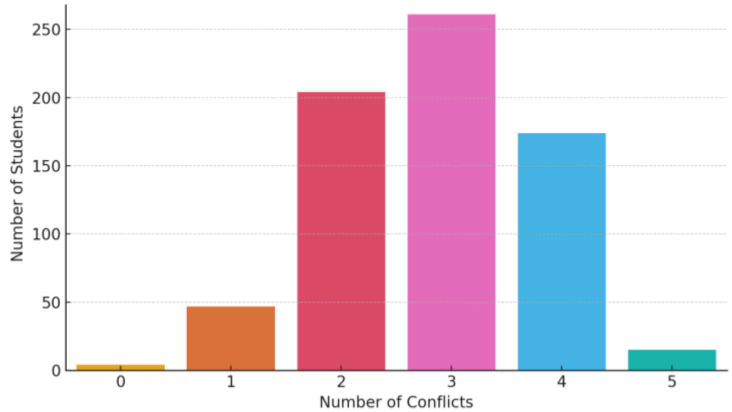

Figure 3 **Distribution of Conflicts Over Social Media**

Figure 3 displays a bar chart that visually represents the number of students corresponding to each level of conflict frequency related to social media use. The chart indicates that digital conflicts are a common phenomenon among the student population, with a pronounced peak at three reported conflicts, followed closely by those who experienced two. This distribution highlights that a substantial portion of students face repeated interpersonal challenges stemming from their digital interactions, reinforcing the notion that social media engagement is closely intertwined with real-world social tension.

To further examine behavioral differences by platform, table 3 presents the average values of four key indicators segmented by the most frequently used social media platform. While the table provides detailed quantitative values, it also reinforces behavioral trends observed across platform types. Instagram users exhibit the highest average addiction score (6.55) and one of the lowest mental health scores (6.12). In contrast, users of LinkedIn and LINE reported lower addiction scores and higher mental health outcomes, suggesting that platform type may influence emotional and behavioral impacts.

Table 3 **Average Scores by Most Used Platform**

Most Used Platform	Avg Daily Usage Hours	Sleep Hours Per Night	Mental Health Score	Addicted Score
Facebook	4.51	7.36	6.72	5.67
Instagram	4.87	7.02	6.12	6.55
KakaoTalk	4.73	7.05	6.00	6.00
LINE	3.25	8.35	8.00	3.00
LinkedIn	2.52	7.29	8.00	3.81

Correlation analysis was conducted to explore the strength and direction of relationships among variables. The addiction score was strongly and positively correlated with the number of social media-related conflicts (r = 0.93) and average daily usage hours (r = 0.83), while it was negatively correlated with mental health score (r = –0.95) and sleep duration (r = –0.76). These findings support the hypothesis that higher usage and increased conflict are associated with elevated addiction, while better sleep and mental health mitigate it.

To rigorously assess the predictive capability of the selected behavioral and psychological variables, three regression models Linear Regression, Random Forest Regressor, and XGBoost Regressor were implemented and evaluated. The performance of each model was quantitatively measured using two commonly adopted evaluation metrics in supervised learning: Mean Squared Error (MSE), which captures the average squared difference between actual and predicted values, and the coefficient of determination (R^2 Score), which reflects the proportion of variance in the dependent variable that is explained by the model.

The results of this evaluation are summarized in table 4, which presents a side-by-side comparison of each model's prediction error and overall explanatory power. This table is essential in benchmarking the effectiveness of traditional linear models against more sophisticated ensemble-based algorithms. It allows for a clear understanding of which modeling approach yields the highest accuracy in capturing the complex relationships between students' digital behaviors and their corresponding addiction scores.

Table 4 Model Performance Comparison

Model	Mean Squared Error (MSE)	R^2 Score
Linear Regression	0.126	0.950
Random Forest Regressor	0.029	0.991
XGBoost Regressor	0.026	0.992

After evaluating the predictive performance of all three models, the results indicate that each algorithm exhibits a high degree of accuracy in estimating social media addiction scores based on the chosen set of behavioral and psychological predictors. The Linear Regression model, despite its simplicity and reliance on linear assumptions, achieved a commendable performance with an R^2 value of 0.950, signifying that approximately 95% of the variance in students' addiction scores could be accounted for by the combined influence of average daily social media usage, sleep duration, mental health score, and frequency of social media-related conflicts.

Nevertheless, the ensemble-based models—Random Forest Regressor and XGBoost Regressor—demonstrated superior predictive power by more effectively capturing non-linear relationships and interaction effects among variables. In particular, the XGBoost Regressor outperformed the other models, producing the lowest Mean Squared Error (0.026) and the highest R^2 score (0.992). These values suggest that the XGBoost model was better able to generalize patterns in the data, likely due to its use of gradient boosting and regularization techniques, which reduce overfitting while preserving predictive precision.

In summary, the findings from all three models provide strong empirical support for the relevance of the selected predictors in modeling social media addiction. The consistently high R^2 values across models reinforce the conclusion that digital behavior patterns—particularly those related to usage intensity, sleep deprivation, emotional well-being, and interpersonal conflict—are reliable indicators of addiction risk. Furthermore, the success of machine learning models such as XGBoost highlights the practical value of computational approaches in analyzing and predicting complex psychological phenomena within the broader context of the digital society.

Discussion

The findings of this study provide meaningful insights into the behavioral and psychological dimensions of social media addiction among students, framed within the broader context of the digital society. Through the integration of descriptive analysis, correlation examination, and predictive modeling, the results underscore the significant roles played by daily usage patterns, sleep behavior, mental health, and social conflict in shaping addictive tendencies. Consistent with prior literature, the analysis reveals that higher levels of social media use are positively associated with increased addiction scores. The strong positive correlation between average daily usage hours and addiction score ($r = 0.83$) supports the notion that prolonged exposure to social media environments fosters habitual or compulsive usage behaviors. This aligns with studies suggesting that the reward mechanisms embedded in social platforms—such as likes, notifications, and algorithm-driven content—can reinforce repetitive engagement, particularly among young users.

Equally important is the observed negative relationship between addiction and psychological well-being. The data show a high negative correlation between addiction scores and mental health ($r = –0.95$), indicating that students who are more addicted to social media tend to report poorer mental health outcomes. This supports earlier findings in the field of cyberpsychology, which link excessive digital engagement to heightened anxiety, depression, and stress. Moreover, the negative correlation between sleep duration and addiction ($r = –0.76$) highlights a critical pathway through which addiction manifests—namely, sleep deprivation caused by late-night scrolling, fear of missing out (FOMO), or disrupted circadian rhythms. One particularly novel aspect of this study is the focus on social conflicts as a mediating factor in digital dependency. The positive correlation between the number of interpersonal conflicts and addiction score ($r = 0.93$), supported by the high frequency of reported conflicts (especially 2–3 per student), suggests that social media addiction may not only be a solitary behavior but also a relational stressor. Conflicts may arise from online misunderstandings, constant connectivity demands, surveillance among peers, or emotional overinvestment in online interactions. This finding has important implications for digital literacy programs, which must address not just personal media habits but also the social dynamics of online communication.

From a methodological perspective, the application of three machine learning models has proven effective in modeling addiction behavior. The XGBoost Regressor achieved the highest predictive accuracy ($R^2 = 0.992$), followed closely by the Random Forest and Linear Regression models. The fact that a relatively simple linear model still explains 95% of the variance suggests that the chosen variables are robust predictors of addiction risk. However, the added accuracy provided by ensemble methods highlights the nonlinear complexity underlying digital behavior patterns. Taken together, these findings point to a multifaceted understanding of social media addiction as a consequence of behavioral intensity, emotional vulnerability, and interpersonal tension. In the digital society, where connectivity is both ubiquitous and normalized, identifying early warning signs of addiction and understanding their predictors is crucial. Interventions should target not only screen time reduction but also improvements in sleep hygiene, mental health support, and conflict resolution strategies.

Future research may explore additional variables such as personality traits, academic performance, or type of content consumed. Moreover, qualitative approaches may deepen our understanding of how students perceive and experience digital stress in their daily lives.

Conclusion

The growing prevalence of social media addiction in today's digital society poses significant challenges, particularly among student populations who are among the most active and impressionable users of digital platforms. This study sought to understand the behavioral and psychological predictors of social media addiction by analyzing a dataset comprising 705 students across various countries and academic levels. The research focused on four central variables: average daily usage hours, sleep duration per night, mental health score, and frequency of social media-related conflicts, which were examined through both descriptive and predictive analytics using Linear Regression, Random Forest Regressor, and XGBoost Regressor. The findings demonstrate that social media addiction is not only common but also deeply interconnected with students' daily routines, emotional well-being, and social environments. Most students reported moderate to high addiction scores, with the majority clustered at levels 7 and 8 on a 0–9 scale. The strong negative correlation between addiction and both sleep hours and mental health scores indicates that excessive use of social media contributes to deteriorating psychological conditions and disrupted sleep patterns. This aligns with previous literature that associates digital overuse with anxiety, depression, and poor sleep hygiene.

Equally concerning is the high prevalence of social conflicts linked to social media usage. A substantial number of students reported experiencing interpersonal tensions, with 261 students indicating three conflicts and 204 students reporting two. These findings suggest that digital engagement is not merely a solitary activity but one that carries considerable relational risks, such as misunderstandings, cyber surveillance, emotional dependency, and social comparison, all of which may exacerbate stress and lead to a cycle of compulsive usage. The application of machine learning models provided strong validation for the predictive power of the selected variables. While the Linear Regression model explained 95% of the variance in addiction scores (R^2 = 0.950), the more advanced ensemble models, particularly XGBoost (R^2 = 0.992, MSE = 0.026), delivered superior performance by capturing non-linear relationships and interactions among features. These results underscore the value of data-driven approaches in behavioral research, offering scalable and interpretable tools for early identification of at-risk individuals.

In conclusion, this study contributes to a more nuanced understanding of social media addiction as a multifaceted behavioral phenomenon that reflects a blend of individual habits, emotional states, and interpersonal dynamics. The findings highlight the importance of holistic intervention strategies that go beyond limiting screen time. Effective solutions should incorporate digital literacy education, sleep hygiene promotion, mental health support, and social-emotional skill development.

Moreover, these insights have practical implications for educators, policymakers, mental health professionals, and digital platform designers. For instance, schools and universities can implement targeted awareness programs and monitoring tools, while app developers can explore ethical interface designs that promote mindful usage and reduce compulsive behavior.

Declarations

Author Contributions

Conceptualization: R.A.M.A. and A.A.A.; Methodology: R.A.M.A.; Software: A.A.A.; Validation: R.A.M.A. and A.A.A.; Formal Analysis: R.A.M.A. and A.A.A.; Investigation: R.A.M.A.; Resources: R.A.M.A.; Data Curation: R.A.M.A.; Writing Original Draft Preparation: R.A.M.A. and A.A.A.; Writing Review and Editing: R.A.M.A. and A.A.A.; Visualization: A.A.A.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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