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Social media addiction: A comprehensive state of mental health

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ABSTRACT

Social media addiction, characterized by compulsive and excessive engagement with social platforms, negatively impacts mental health by fostering unfavorable comparisons between users' lives and the idealized portrayals of others. These curated online personas can distort self-perception, diminish self-esteem, and contribute to long-term psychological distress. While social media offers networking and support, its detrimental effects necessitate a balanced approach to usage. This study investigates the relationship between social media addiction and mental health outcomes using a synthetic dataset, revealing a strong negative correlation (r = -1.0) between addiction severity and mental well-being. A Random Forest model was employed to predict mental health scores based on addiction levels, demonstrating the predictive utility of behavioral engagement metrics. The findings underscore the need for targeted interventions to mitigate the adverse mental health consequences of social media addiction, suggesting that structured approaches could help reduce its psychological burden.

1. Introduction

Social media platforms have significantly transformed the ways people interact, learn, and spend their leisure time, becoming an essential part of daily life (Hou et al., 2019). However, their widespread use has also raised concerns about excessive use and potential addiction. While these platforms provide valuable opportunities for communication and access to information, they may also contribute to problematic behaviors. The term social media addiction is considered a form of internet addiction, alongside related issues such as information overload, online gaming addiction, online shopping and trading compulsions, smartphone addiction, cybersexual addiction, and others.

Addictive use of social media is often reinforced by the continuous desire for social approval, acceptance, and feedback. Excessive use can damage personal relationships, lower academic achievement, reduce productivity, and lead to fear of missing out (FOMO) (Talan et al., 2024). Although social media may provide community and emotional support, prolonged use has been linked to various mental health problems, including depression, anxiety, and low self-esteem.

Globally, social media use is rapidly increasing. While there were already 2.03 billion users, this figure was expected to grow to 2.67 billion by 2018 due to advances in digital technologies, including smartphones and wearable devices (Wang and Shang, 2024). Social media accounted for 28% of overall media consumption, with users aged 15–19 spending an average of three hours daily, and those aged 20–29 spending nearly two hours daily (Sun and Zhang, 2021).

On a global scale, approximately 5 million photos are uploaded to Instagram every day, more than 500 million tweets are posted, and a significant proportion of users report dependency on these platforms: 18% state they cannot stay away from Facebook for even a few hours, while 16% rely on Facebook or Twitter for their morning news (Chen, 2019). Understanding the psychological processes

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that contribute to social media's addictive qualities is crucial for comprehending its compelling and potentially addictive nature (Mercan and Uysal, 2023). Social media platforms evoke people's need for approval and social belonging through social comparison, self-presentation control, and fear of missing out (FOMO), leading to a cycle of seeking acceptance and obsessive checking and participation (Mim et al., 2024). Social Media Addiction is influenced by cognitive biases, such as attentional bias, confirmational bias, and accessible cascade. It can lead to escapism, mood modification, dissociation, and cognitive load. To escape from their daily life problems, to regulate their mood and escape from stress, people tend to rely on social media (Brevers and Turel, 2019).

Overuse can cause anxiety, depression, and lower self-esteem with recurring thoughts of body image problems. Studies show that seeing idealized material and social comparison lead to greater self-consciousness and unpleasant emotions (Turhan Gürbüz et al., 2021). It can also decrease our circadian rhythms, leading to poor quality of sleep and abnormal tiredness because consuming social media content is a mindless, brain-numbing task. Social media addiction can result in reduced productivity and academic performance, compromised abilities to control impulsivity or make wise decisions, as well as potential social isolation (Aksoy, 2018).

This may lead to distractions, a focus challenge, or interpersonal stress. The increased focus on virtual connections can compromise the quality of in-person social support and meaningful relationships, affecting overall well-being and long-term goals (Leong et al., 2019).

Through campaigns in print and digital media, governments can raise public awareness about the negative effects of social media use. Similarly, the Curriculum Development Center may integrate relevant information into textbooks and learning materials to educate students. Parents also play an important role by monitoring their children's social media use and providing appropriate guidance to prevent addiction. In addition, promoting healthy digital habits can help reduce the risks associated with excessive use. Such habits include setting time limits, taking regular breaks, and engaging in alternative activities (Gori et al., 2023).

To encourage responsible social media use and reduce any unfavorable effects, it is essential to comprehend these dynamics. The scale and complexity of social media data are expanding, making it challenging to discover precise patterns of user behavior and addiction using standard analytical methods. This is where machine learning (ML) and artificial intelligence (AI) come into play. They offer powerful methods for sorting through vast volumes of data and identifying minute patterns that individuals may not recognize (Varma et al., 2024).

This study aims to examine the relationship between social media addiction and its effects on mental health, particularly in relation to self-perception, confidence, and overall psychological well-being. To achieve this, a Random Forest model will be applied to predict mental health outcomes based on different levels of addiction.

This method is selected because it is robust against overfitting, a potential concern given the use of a synthetic dataset in this study, and because it effectively handles both numerical and categorical data while simplifying complex relationships among multiple variables.

2. Literature review

The recent research provided empirical evidence regarding the negative impact of addiction of social media and mental health in the case of students in colleges and their academic performances (Reyaz et al., 2024). This study was also consistent with the previous studies regarding addiction negatively affecting self-esteem and seeking social validation as indicators of mental disorders, and it was one of the empirical pieces of evidence that suggested that the reliance on external validation mediated the relation of social media addiction to mental health (Aksoy, 2018).

Moreover, the effective implementation of a cognitive-behavioral intervention reduced social media addiction and enhanced mental health and academic productivity (Amirthalingam and Khera, 2024).

Notably, one of the studies demonstrated that a reduction in mental health wellbeing because of addiction to social media is said to happen partly due to low self-esteem of individuals; it was also shown that the reverse mediation effect of self-esteem on mental health, psychologist, and social media addiction as the outcome variable was not found to be significant.

2.1. Impact of addiction to social media on mental health

Several negative mental health effects have been associated with overexposure to social media, including increased anxiety and depressive symptomatology. The studies conducted established a positive correlation between highly elevated usage of social media and such issues, mostly on grounds of constant exposure to idealized content and social comparison, which promotes poor self-esteem and a sense of inadequacy (Hemalatha et al., 2024; Varma et al., 2024; Yafi et al., 2024; Chauhan et al., 2024; Kumar and Chauhan, 2024).

Furthermore, lower self-esteem and problems with body image have been linked to the internalization of social media users' representations of conventional beauty standards, especially among younger users. In addition, the stimulating content of social media and the blue light emitted by screens throw off circadian cycles, resulting in less restful sleep, more drowsiness during the day, and general exhaustion.

2.2. Behavioral and cognitive consequences

Excessive use of social media can significantly influence both cognitive functioning and productivity. Research indicates a negative relationship between social media use and productivity, as frequent interruptions and distractions reduce the ability to concentrate and complete tasks. Moreover, social media addiction may weaken impulse control and decision-making, leading to difficulties in self-regulation and achieving personal goals. Heavy use of social media can also contribute to social isolation and place strain on real-life relationships, since increased reliance on virtual interactions often diminishes the quality of face-to-face communication and hinders the development of strong interpersonal connections.

2.3. Theoretical models of social media addiction

Different theoretical models explain how social media addiction develops and persists. Cognitive-behavioral models suggest that addiction is reinforced by distorted emotions, attitudes, and behaviors. These theories argue that dysfunctional beliefs and cognitive biases can promote compulsive use of social media, thereby maintaining the cycle of addiction. In contrast, the biopsychosocial model provides a wider view, emphasizing the interaction of biological, psychological, and social factors in shaping addictive behavior. Additionally, the uses and gratifications theory highlights how individual motivations and unmet psychological needs, such as the search for entertainment or opportunities for self-expression, influence patterns of media use (Sun and Zhang, 2021).

2.4. Interventions and strategies

Several interventions and strategies have been proposed for addressing social media addiction. One of the most widely used approaches is cognitive-behavioral therapy, which focuses on the problematic thoughts, emotions, and behaviors associated with excessive use. This method helps individuals develop healthier coping strategies and improve their self-regulation skills. Another effective approach combines mindfulness-based practices with temporary abstinence from social media, enabling users to become more aware of their online habits and to adopt a more balanced and intentional use of digital platforms (Ji et al., 2023). In addition, parental guidance and education play an important role, particularly for younger users.

3. Methodology

3.1. Dataset overview

This study makes use of the “Time-Wasters on Social Media” dataset, a large synthetic dataset designed to reflect real patterns of social media use. It contains 32 variables covering self-reported behaviors, content consumption, platform engagement, and user demographics. The dataset provides detailed insights into how individuals interact with social media platforms. Key variables include the type of platform (e.g., Facebook, Instagram, TikTok), total time spent, and number of sessions, which indicate the frequency and intensity of use. In addition, video-specific information is recorded, such as Video ID, category (e.g., entertainment, gaming), length, engagement metrics (likes and comments), and an importance score measuring the perceived relevance of the video to the user. The dataset also tracks the number of videos viewed and the total time spent watching them.

The dataset also includes detailed user behavior metrics such as scroll rate, login frequency, productivity loss due to social media use, content satisfaction, reasons for watching, device type, operating system, watch time, self-control, and addiction level. Additional variables, such as current activity and connection type, are also recorded. For analysis, the dataset was imported into the environment using the Python Pandas library, which is well-suited for managing large and complex datasets. It also facilitates feature engineering and data preprocessing, providing a foundation for the subsequent stages of this study.

3.2. Data preprocessing

Data preprocessing was carried out to ensure the dataset’s quality and consistency before analysis. Missing values were handled using the pandas library’s fillna function, where absent entries were replaced with the mean of the respective column to reduce the impact of incomplete data. Outliers were then identified using the SciPy library’s zscore function, with values exceeding plus or minus three standard deviations removed from the dataset. Finally, the preprocessing stage concluded with the separation of feature variables and the creation of a new series containing only the addiction level column, which was used as the target variable for the predictive model.

3.3. Feature engineering

The model’s predictive power was improved through feature engineering, which involves creating new features from existing ones. Three new features were derived: Average Time Spent by dividing the total time spent on videos by the number of sessions, Average Videos Watched by dividing the total number of videos watched by the number of sessions, which will help in analyzing the content consumption, and Average Engagement by dividing the total engagement by the number of video views for analyzing their engagement level. Such features offer a more thorough understanding of user engagement with video content, as well as a deeper knowledge of user behavior and video consumption trends.

3.4. Correlation analysis

We performed a correlation analysis, which helps in finding the factors that are most strongly associated with social media addiction levels, which further helps in feature selection in the predictive model phase. A correlation matrix was computed using the Pearson correlation coefficient (r) to analyze relationships between Addiction level and mental health score.

3.5. Feature selection

In order to identify the most significant predictors within the dataset, a feature selection process was done using correlation analysis. This analysis between each feature and addiction level was computed; hence, the top 10 features with the highest correlation were selected for further analysis.

3.6. Model training and evaluation

A Random Forest Classifier was developed to predict social media addiction levels based on influential features. The steps include splitting the dataset into 80-20 as training and testing sets, with 100 decision trees trained on selected features. The model was then used to predict addiction levels on the testing set, with its performance evaluated using an accuracy score and a classification report.

3.7. Analyzing the effect on mental health

To examine the impact on mental health, a composite metric called Mental Health Score was created by summing three key variables: Satisfaction, Productivity Loss, and Self-control. This score was designed to represent different aspects of mental health in a single measure. After generating the Mental Health Score, a correlation analysis was performed to study its relationship with the addiction level.

4. Results

In this study, a synthetic dataset was used that includes features related to social media usage, user demographics, and self-reported mental health indicators. The dataset was divided into features and labels, where the labels represent the target outcomes: the user's addiction level and mental health score. A random forest classifier was chosen as the predictive model because it is robust, suitable for multi-class classification, capable of handling high-dimensional data, and less likely to overfit. Random forest is a well-known ensemble learning method that builds multiple decision trees during training and combines their results by taking either the majority class (mode) or the average prediction. This section provides a brief explanation of the prediction model's results.

4.1. Correlation findings

The study found a strong positive correlation between "Addiction Level" and "Satisfaction," suggesting that individuals with higher addiction levels report higher satisfaction (r = 0.995). However, other variables showed weaker correlations, with "Average Time Spent" and "Average Videos Watched" showing weak positive correlations. Age, engagement, Video ID, importance score, total time spent, and number of videos watched all exhibited weak positive correlations, suggesting that these factors have minimal influence on the addiction levels.

Age, engagement, Video ID, importance score, total time spent, and number of videos watched all exhibited weak positive correlations, suggesting that these factors have minimal influence on the addiction levels, as shown in Table 1.

Table 1: Correlation of variables with addiction level

Variable	Correlation with addiction level (r)
Addiction level	1.000
Satisfaction	0.995
Average time spent	0.079
Average videos watched	0.076
Age	0.033
Engagement	0.028
Video ID	0.021
Importance score	0.018
Total time spent	0.016
Number of videos watched	0.013

4.2. Performance of the random forest classifier

When the Random Forest classifier was applied to the dataset, it achieved a perfect score across all classes. The classification report shows that each class (0 to 7) obtained a precision, recall, and F1-score of 1.0. However, in real-world scenarios, datasets usually contain inconsistencies such as missing values, outliers, and variations in user behavior, which can reduce the model's performance. In order to delve deeper into the evaluation metrics, we will cover:

- Precision is the measure of how many positively predicted and a precision of 1.0 indicates that the model has perfectly predicted every instance belonging to the given class.
- Recall is the measure of how many positive instances were detected by the model. A recall equal to 1.0 means that every single instance of the particular class was detected by the model.
- F1-score is defined as the weighted average of precision and recall, where the average is computed using their harmonic mean. It derives and serves a purpose as a metric useful when both false positives and false negatives have to be taken into consideration.

Support is the count of the actual instances of each class present in the dataset. It adds perspective to the rest of the metrics since a higher support means more samples were present for that class. Perhaps in this particular case, all the classes had sufficient support for the model to learn the pattern, thereby resulting in the perfect scores.

Nonetheless, it should be considered that this performance could be primarily attributed to the fact that the dataset is synthetic in nature. Synthetic data sets are usually produced with little to no background noise and genre variation, making it easy for any model employed to learn and classify accurately. Even though these findings illustrate that the Random Forest classifier was effective in classifying this specific dataset, these results may not be applicable to situations in the real world where the data is more complex.

Further details are presented in the classification report (Table 2), where each class (0 through 7) received a score of 1.0 for precision, recall, and F1-score, but in the real-world scenarios the data is often characterized by a number of inconsistencies such as missing values, outliers, and sometimes a different behavioral invariability which hinders the performance of the model.

Table 2: Classification report metrics for random forest classifier

Class	Precision	Recall	F1-score	Support
0	1.00	1.00	1.00	37
1	1.00	1.00	1.00	8
2	1.00	1.00	1.00	41
3	1.00	1.00	1.00	33
4	1.00	1.00	1.00	6
5	1.00	1.00	1.00	37
6	1.00	1.00	1.00	10
7	1.00	1.00	1.00	8

4.3. Correlation analysis of mental health score

Table 3 provides the strength and direction of the linear relationship between the two variables. Correlation between the level of addiction and the score on the mental health test shows a perfect correlation at -1.0. This indicates that as the addiction level increases, the mental health score decreases in a perfectly linear relationship and vice versa, and the direction and intensity of the linear association between the addiction level and mental health score are displayed in Table 3. The research finds that the largest conceivable negative association, with a correlation coefficient of -1.0, exists. This indicates that the two variables have a fully inverse linear connection, but it should be noted that the observed perfect correlation ($r = -1.0$) between addiction level and mental health score, as well as the classification accuracy of 100%, are indicative of the dataset's synthetic nature. Synthetic datasets often lack the noise and variability typical in real-world data, resulting in overly idealized outcomes.

These findings should be interpreted as theoretical benchmarks rather than practical conclusions applicable to diverse real-world scenarios. In real-world scenarios, different factors such as environmental stressors, individual resilience, and support systems may moderate this relationship. Incorporating variability in future studies would enhance the generalizability of the results.

The scatter plot (Fig. 1) in which the data points form a straight line with a declining trend graphically supports this conclusion. Higher addiction levels are frequently linked to lower mental health scores, as the plot illustrates, underscoring the significant inverse association between these two factors.

Table 3: Correlation between addiction level and mental health score

Variable	Addiction level	Mental health score
Addiction level	1.0	-1.0
Mental health Score	-1.0	1.0

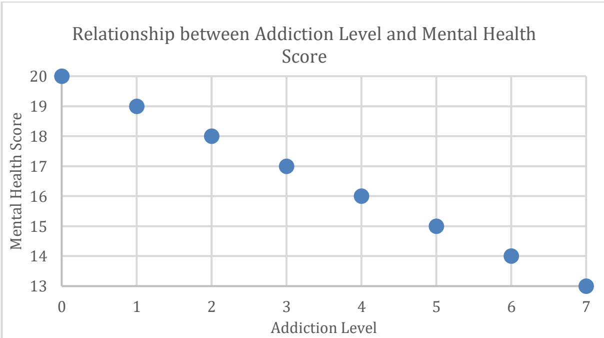

Fig. 1: Relationship between addiction level and mental health score

In actual terms, there is a direct and proportional reduction in an individual's mental health score as their level of social media addiction rises. On the other hand, a decline in addiction equals a corresponding improvement in the mental health score. The correlation coefficient of -1.0 signifies a highly consistent and predictable association between the rise in social media addiction and the decline in mental health for every unit increase in social media addiction.

The significance of tackling social media addiction to enhance mental well-being is shown by this perfect negative connection, which implies that social media addiction plays a major role in declining mental health.

5. Conclusion

In the digital era, social media platforms have become a central part of daily life, shaping how individuals interact, communicate, and access information. The extensive use of these platforms has transformed them from simple communication tools into cultural forces that influence public opinion, consumer behavior, and mental health. This study explores the relationship between social media addiction and mental health by applying analytical methods to synthetic data. The results reveal a negative correlation between addiction levels and mental health scores, suggesting that higher addiction is associated with poorer mental health outcomes.

The Random Forest classification model achieved perfect accuracy in predicting different levels of social media addiction and their corresponding effects on mental health. However, these results cannot be directly generalized to real-world situations because synthetic datasets are controlled and do not reflect the complexities of actual human behavior. The perfect correlation and classification observed here represent the idealized nature of the dataset rather than realistic outcomes. Future research will focus on collecting real-world and real-time data to validate these findings and to uncover more complex patterns in user behavior and mental health. Such studies will also consider ethical aspects of data collection and propose strategies to reduce the negative effects of social media addiction.

This study suggests that interventions can be developed to help individuals reduce addictive use of social media while promoting responsible engagement. Raising awareness and designing effective strategies to maximize the benefits of social media while minimizing its risks to emotional well-being remain key objectives. Ultimately, this research seeks to ensure that social media contributes positively to the quality of life of present and future generations.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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