

Social Media Usage and Emotional Well-being: An Analytical Perspective

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Abstract—The rapid growth of social media platforms has transformed communication, interaction, and information sharing, particularly among students and young adults. While social media offers connectivity, entertainment, and knowledge exchange, excessive and uncontrolled usage may negatively influence emotional well-being through stress, anxiety, low self-esteem, emotional instability, online comparison, and prolonged digital engagement. This study analyzes the relationship between social media usage patterns and emotional well-being using statistical and analytical approaches. The research examines factors such as time spent on social media, platform preference, frequency of use, and engagement patterns in relation to emotional indicators including happiness, stress, anxiety, self-esteem, emotional exhaustion, and overall well-being. Primary data were collected through a structured online questionnaire from 85 respondents. Descriptive analysis, correlation analysis, and Logistic Regression were used to identify behavioral patterns and predict emotional well-being categories. The results indicate a strong relationship between social media addiction and emotional well-being, with higher addiction levels associated with lower emotional well-being. The Logistic Regression model achieved 94% overall accuracy in the reported classification results. The study highlights the importance of balanced social media usage and provides data-driven recommendations for healthier digital habits.

Index Terms—emotional well-being, logistic regression, social media, social media addiction.

I. INTRODUCTION

The rapid growth of internet accessibility and digital technologies has made social media an integral part of everyday life, particularly among students and young adults. Platforms such as Facebook, Instagram, WhatsApp, Snapchat, and Twitter/X enable users to communicate, share information, express themselves,

and build virtual communities. While social media offers several benefits, excessive or unhealthy usage may negatively affect emotional well-being by contributing to stress, anxiety, loneliness, and reduced self-esteem.

Emotional well-being refers to an individual's ability to manage emotions, cope with daily challenges, maintain positive relationships, and experience overall psychological satisfaction. Social media usage can influence emotional well-being through factors such as time spent online, frequency of use, social comparison, online interactions, and social validation. However, balanced usage may also provide social support, connectivity, and opportunities for self-expression.

With the increasing availability of behavioral data, ****Business Analytics**** provides useful statistical and analytical techniques for examining the relationship between social media usage and emotional well-being. This study analyzes social media usage patterns and their association with emotional well-being using data-driven methods. The findings aim to identify significant behavioral factors, provide meaningful insights into digital habits, and support awareness of responsible and balanced social media usage among students and young adults.

II. LITERATURE REVIEW

Social media usage has increased rapidly over the past decade, attracting significant academic attention regarding its influence on emotional and psychological well-being. Various researchers have examined both positive and negative outcomes of

social media engagement, highlighting the complexity of its impact on individuals.

[2] did a comprehensive review on the link between social media and mental health. The study found that excessive social media use is linked to mental health issues such as stress, anxiety, and depression. The review also emphasized that online interactions can influence emotional stability, especially among young individuals who spend considerable time on social networking platforms.

According to [3] review of the literature on social media and mental health, young adults now use social media extensively as a recreational activity because of its many platforms and ease of access. According to their findings, excessive social media use may cause behavioral changes and psychological distress, highlighting the need for more study to fully comprehend its emotional effects.

In their 2025 study on the effects of social media on teenage mental health, Noya, J., and Lameky, V. Y. identified a number of contributing factors, including cyberbullying, FOMO, social comparison, and excessive screen usage. The study concluded that these factors significantly affect emotional well-being and may result in anxiety, loneliness, and reduced self-confidence among users.

[6] looked at the connection between university students' use of social media and psychological health. Self-esteem and online social support were found to be moderating factors in their study. The research found that social media can influence emotional well-being positively or negatively depending on how individuals use these platforms. The study further indicated that cyberbullying may weaken positive psychological outcomes associated with social media engagement.

A study that was published in [7] examined the relationship between young people's subjective well-being and their everyday use of social media. According to the study, using social media frequently is associated with lower emotional well-being and a diminished sense of self-worth. Additionally, it was discovered that upward social comparisons—in which people evaluate themselves against those they consider to be more attractive or successful—have a major detrimental impact on emotional well-being.

A comprehensive review and meta-analysis on the connection between social media use, mental health, and sleep quality was carried out by [8]. Although the study's findings were mixed, it appeared that younger

people are more likely to be impacted by excessive social media use, especially in terms of sleep disturbances and psychological discomfort.

Another large-scale systematic literature review analyzing data from over 571,000 participants across multiple countries found that daily social media usage is strongly associated with increased stress, anxiety, depression, loneliness, and poor sleep quality. The study emphasized that frequent exposure to social media content can influence both emotional and physical health.

[7] used secondary research data to investigate the connection between teenage mental health and social media use. Negative emotional effects like despair, anxiety, and low self-esteem were found to be strongly correlated with excessive social media use. However, it also noted that the relationship varies depending on individual behavior patterns and environmental factors.

[8] conducted a meta-analysis exploring the relationship between social media use and positive well-being outcomes. The study concluded that the effect of social media on emotional well-being depends largely on the type of usage. Active engagement, such as communication and content creation, may enhance well-being, while passive browsing and comparison behaviors are more likely to produce negative emotional outcomes.

Recent research focusing on adolescents' experiences with social media found that users often report both positive and negative outcomes simultaneously. While many individuals use social media to build relationships and seek information, others report negative experiences such as body shaming and privacy concerns. The study suggested that the overall emotional impact of social media varies across platforms and user behavior.

One of the most used statistical and predictive analytical methods for analysing correlations between variables is linear regression. It aids researchers in comprehending how a dependent variable is influenced by one or more independent variables. In studies related to behavioral science and social media analytics, linear regression is commonly used to measure the impact of usage patterns on psychological and emotional outcomes.

[9] explained that linear regression is an effective statistical tool used to analyze relationships between dependent and independent variables and to predict

outcomes based on observed data patterns. The authors highlighted that regression models help in identifying significant predictors and measuring the strength of relationships, making them highly useful in social and behavioral research.

[10]. used correlation analysis and multiple regression in the behavioural sciences. According to Routledge, research in psychology and social science frequently uses linear regression to assess how various behavioural aspects affect people's feelings and views. The study highlighted that regression analysis helps researchers quantify the effect of multiple variables simultaneously and interpret their individual contributions to the dependent variable.

[11] discussed regression analysis as an essential multivariate analytical technique in business research. According to their research, linear regression helps in understanding consumer behavior, decision-making patterns, and emotional responses. The study highlighted that regression models provide data-driven insights and support evidence-based decision-making, which is highly relevant in Business Analytics studies. [12] employed regression analysis in the context of social media research to examine how online social networking affects teenage well-being. Their findings suggested that regression models effectively identify how different social media activities influence self-esteem and emotional stability among users.

Similarly, [13] applied regression analysis to examine the relationship between Facebook usage and emotional well-being. The study found that increased social media usage predicted declines in subjective well-being over time. The research demonstrated how regression analysis can be used to measure behavioral influences on emotional health.

[14] used regression models to study the impact of social comparison on Facebook and its relationship with depression. Their findings suggested that passive social media consumption significantly predicts negative emotional outcomes. The study confirmed that regression techniques are useful in analyzing behavioral data and identifying significant psychological predictors.

Regression analysis has also been used in recent digital behavioural analytics studies to examine user engagement and emotional health. Regression analysis was used by [15] to investigate the relationship between social media use and perceived social

isolation. According to the study's findings, young adults who use social media more frequently are more likely to experience social isolation.

Regression models are particularly useful in this study because they help measure how different social media usage factors such as time spent, frequency of use, and engagement type influence emotional well-being indicators. The technique allows researchers to quantify relationships and identify key predictors affecting emotional health outcomes.

Relevance of Linear Regression to the Present Study
Based on previous research, linear regression is considered an appropriate analytical tool for examining the relationship between social media usage and emotional well-being. The model helps in identifying the extent to which usage patterns influence emotional responses and supports data-driven interpretation of behavioral trends. Therefore, linear regression is applied in this study to analyze survey data and determine significant factors affecting emotional well-being.

Summary of Literature Gap

The review of existing studies shows that social media has a significant but complex relationship with emotional well-being. While many studies highlight negative psychological effects, others emphasize positive social support and connectivity benefits. However, there is still a need for data-driven analytical research focusing on specific usage patterns and emotional outcomes among students. This study aims to address this gap by applying statistical and business analytics techniques to examine the relationship between social media usage and emotional well-being.

III. OBJECTIVE OF THE STUDY

1. Problem Definition

People's daily lives, especially those of students and young adults, have been profoundly impacted by the growing use of social media platforms. Although social media offers chances for communication, amusement, and information exchange, excessive and uncontrolled use may have a detrimental impact on mental health. Many users experience stress, anxiety, low self-esteem, and emotional instability due to prolonged social media engagement, online comparisons, and digital interactions.

However, there is limited data-driven understanding of how different patterns of social media usage, such as time spent, frequency of use, and type of engagement, impact emotional well-being. Therefore, this study aims to analyze and identify the relationship between social media usage and emotional well-being using analytical and statistical

2. Objectives

To analyze the relationship between social media usage patterns and emotional well-being, and to examine how factors such as time spent, platform preference, and type of engagement influence emotions like happiness, stress, anxiety, self-esteem, and overall mental well-being. To analytically study the impact of social media usage on emotional well-being using data-driven and statistical techniques. The objectives for the study are as follows-

1. To examine social media usage patterns such as frequency, duration, and preferred platforms among users.
2. To analyze the relationship between social media usage and emotional factors like happiness, stress, anxiety, self-esteem, and overall mental well-being.
3. To identify key usage behaviors that significantly influence emotional well-being.
4. To apply statistical and analytical methods to interpret survey data and uncover meaningful insights.
5. To provide data-backed recommendations for healthier and more effective social media usage.

IV. RESEARCH METHODOLOGY

The study adopts a descriptive and analytical research design to examine the relationship between social media usage patterns and emotional well-being. A quantitative approach is used to analyze the collected data and identify significant patterns and relationships.

A. Nature of Data and Data Collection

The study uses primary and secondary data. Primary data was collected through a structured online questionnaire using Google Forms. The questionnaire consisted mainly of close-ended and Likert-scale questions covering social media usage, including daily time spent, frequency of use, and preferred platforms. Emotional well-being was assessed using indicators such as happiness, stress, anxiety, and self-esteem.

Secondary data was obtained from research papers, journals, books, reports, and reliable online sources to support the theoretical framework and interpretation of findings.

B. Sampling Design

- Population - The target population comprises active social media users from different age groups and backgrounds. Since it is not feasible to survey the entire population, a sample was selected for the study.
- Sample Size - The study collected responses from 85 respondents. The sample size was determined based on respondent accessibility, time constraints, and the scope of the study.
- Sampling Technique - The study uses convenience sampling, a non-probability sampling technique in which respondents are selected based on their accessibility and willingness to participate. Students, peers, and other active social media users were approached through online platforms.

Convenience sampling was selected because it enables quick, cost-effective, and accessible data collection through Google Forms. Although it may limit the generalizability of the findings, it is suitable for an exploratory academic study.

C. Business Analytics Tools and Techniques

The collected data was analyzed using the following statistical and analytical techniques:

- Descriptive statistics: Mean, percentage, and standard deviation
- Graphical analysis: Bar charts and pie charts
- Correlation analysis: To examine relationships between social media usage and emotional well-being
- Regression analysis: To assess the influence of social media usage variables on emotional well-being

D. Scope of the Study

The study focuses on analyzing the relationship between social media usage behavior and emotional well-being, particularly with respect to time spent, frequency of usage, platform preference, happiness, stress, anxiety, and self-esteem. The findings are limited to the selected respondents and study period.

E. Limitations of the Study

The study has the following limitations:

The data is based on self-reported responses, which may involve response bias.

The small sample size and convenience sampling limit the generalizability of the findings.

Emotional well-being is subjective and may vary across individuals.

The study examines associations between variables and does not necessarily establish causal relationships.

V. DATA ANALYSIS AND RESULTS

The application of Logistic Regression in this study provides valuable analytical insights into behavioral patterns associated with social media usage. It helps in identifying risk factors related to excessive social media engagement and offers a data-driven approach to understanding its psychological implications. The findings derived from this predictive model can assist researchers,

mental health professionals, and policymakers in developing awareness programs and strategies to promote healthier digital habits and improve emotional well-being among social media users.

1. Dataset Description

The dataset used in this study was collected through a structured questionnaire focusing on social media usage behavior and emotional well-being indicators. The dataset consists of multiple variables representing user responses based on Likert scale measurements and categorical emotional indicators. The description of the variables is given in the table 1. The dataset was imported into Python using the Pandas library. The dataset included responses regarding:

- Anxiety when unable to check social media
- Impact of social media on self-esteem
- Effect of social media usage on sleep pattern
- Emotional exhaustion caused by social media

These variables were used to construct addiction and emotional well-being indicators.

2. Data Preprocessing

Data preprocessing is an important step in data analysis and data mining that involves preparing raw data for further processing and analysis. In real-world datasets, the collected data is often incomplete, inconsistent, noisy, or contains missing values. Data

preprocessing helps improve the quality and reliability of the data by performing tasks such as data cleaning, data integration, data transformation, and data reduction. Data cleaning removes errors and handles missing or incorrect values, while data transformation converts data into a suitable format for analysis. Data reduction

helps reduce the size of the dataset without losing important information. Overall, data preprocessing ensures that the dataset becomes accurate, consistent, and suitable for building analytical or machine learning models. The following preprocessing techniques were applied:

Removal of Personal Identifiers

Personal information such as Timestamp, Email Address, and Name was removed from the dataset to maintain respondent privacy and ensure that these variables do not affect the analysis.

3. Data Cleaning

The dataset was cleaned by removing unnecessary columns and ensuring that only relevant variables required for the study were retained.

• Handling Missing Values

The dataset was checked for missing values using `isnull()` and rows containing missing values were removed using the `dropna()` function to maintain data consistency.

• Column Renaming / Data Formatting

Column names were cleaned by removing extra spaces, special characters, and replacing spaces with underscores to make them easier to use during analysis.

4. Data Verification

The dataset structure was verified using functions such as `head()`, `shape`, and `info()` to understand the dataset and confirm successful preprocessing.

5. Data Export / Storage

The cleaned dataset was saved as a CSV file so that it could be used for further analysis and modeling.

6. Encoding of Likert Scale Responses

Survey responses such as Strongly Agree, Agree, Neutral, Disagree, and Strongly Disagree were converted into numerical values to enable statistical analysis.

7. Correlation Analysis

Correlation analysis assesses the strength and direction of a link between many variables. This study uses correlation analysis to explore the relationship between social media addiction and emotional well-being among users. This analysis aims to evaluate if growing social media use and addiction affect users' emotional health.

Correlation indicates whether two variables move in the same direction (positive correlation), opposite direction (negative correlation), or there is no relationship between them. Correlation coefficients range from -1 to +1, with +1 indicating a strong positive association, -1 indicating a strong negative relationship, and 0 indicating no meaningful relationship between variables.

In this research, variables related to social media addiction such as daily time spent on social media, frequency of usage, dependency levels, and emotional attachment to social media platforms are analyzed against emotional well-being indicators such as stress, emotional exhaustion, mood changes, and overall psychological satisfaction. The Pearson correlation method is generally applied when variables are numerical and normally distributed, while Spearman rank correlation can be used when the data is ordinal or not normally distributed. Since most survey responses are categorical or ordinal in nature, appropriate encoding techniques are used before performing correlation analysis.

The correlation results help in identifying patterns within the dataset. A positive correlation between social media addiction and emotional exhaustion would indicate that increased usage is associated with higher emotional stress and fatigue. Conversely, a negative correlation between balanced usage and emotional distress would suggest that moderate or controlled social media engagement may support better emotional well-being. These findings provide a preliminary understanding of the relationships between variables before applying advanced predictive models such as Logistic Regression.

Furthermore, correlation analysis assists in feature selection for the predictive model by identifying variables that have strong relationships with emotional well-being. Variables showing weak or insignificant correlation can be excluded to improve model accuracy and reduce complexity. This process enhances the efficiency and reliability of the

classification model developed in later stages of the study. Overall, correlation analysis plays a crucial role in understanding behavioral trends and relationships between social media addiction and emotional health. The insights obtained from this analysis contribute to identifying key influencing factors and support the development of strategies to promote healthier social media usage habits among users.

a. Interpretation of Correlation Heatmap

The correlation heatmap shows how demographic, behavioral, and psychological characteristics impact social media consumption and emotional well-being. The heatmap's values vary from -1 to +1, with +1 indicating a strong positive association, -1 indicating a strong negative relationship, and 0 indicating weak or no relationship between variables.

- Relationship between Social Media Addiction and Emotional Well-being

The heatmap shows a moderate negative association between social media use/addiction indicators and emotional well-being. Research indicates that excessive social media use or addiction might lead to decreased emotional well-being. It indicates that excessive engagement with social media may contribute to emotional stress, mood disturbances, or reduced psychological satisfaction among users.

- Emotional Exhaustion and Social Media Usage

There is a positive correlation between time spent on social media and emotional exhaustion indicators. This implies that users who spend more time on social media are more likely to experience emotional fatigue and mental strain. This supports the research assumption that prolonged exposure to social media content may negatively affect emotional health.

- Self-Comparison and Appearance Pressure

The analysis also shows a positive relationship between social media usage and self-comparison or pressure to appear perfect online. This suggests that individuals who frequently use social media platforms tend to compare themselves with others, which can influence self-esteem and emotional stability.

- Demographic Variables

Demographic factors such as age, occupation, and educational qualification show weak correlations with emotional well-being and social media addiction. This indicates that emotional effects of social media usage are not strongly dependent on demographic

characteristics and may affect users across different age groups and backgrounds.

- Time Management and Usage Control

Variables related to usage control, such as setting time limits or reducing screen time, show slight positive relationships with emotional well-being. This suggests that users who regulate their social media usage tend to experience better emotional balance and reduced psychological distress.

- Overall Interpretation

The correlation analysis highlights that social media addiction and excessive usage patterns are associated with negative emotional outcomes such as exhaustion, stress, and reduced well-being. While the relationships are moderate rather than extremely strong, they clearly indicate behavioral patterns linking social media engagement with psychological health. These findings provide statistical support for further predictive modeling using Logistic Regression and help identify key influencing variables for emotional well-being.

1. Multivariate Analysis and Addiction Level Calculation

Multivariate analysis refers to the statistical examination of more than two variables simultaneously to understand complex relationships within a dataset. In this study, multivariate analysis is used to examine the combined effect of multiple independent variables—such as time spent on social media, frequency of usage, emotional exhaustion, self-comparison behavior, sleep disturbance, and productivity impact—on the dependent variable, emotional well-being.

Unlike univariate or bivariate analysis, multivariate techniques provide deeper insights by identifying how several factors interact together. In this research, correlation analysis and Logistic Regression are applied as part of the multivariate approach. These methods help determine which factors significantly influence emotional well-being and how strongly social media addiction contributes to psychological outcomes. The multivariate model allows for better prediction accuracy and helps in identifying key behavioral indicators associated with emotional distress. It also supports data-driven decision-making by highlighting the most impactful variables affecting users' mental health.

2. Addiction Level Calculation

The addiction level of respondents is calculated using responses to multiple survey questions related to social

media dependency, compulsive usage, inability to reduce screen time, emotional attachment, and interference with daily responsibilities. Each response is assigned a numerical score based on a Likert scale (for example: Strongly Agree = 5, Agree = 4, Neutral = 3, Disagree = 2, Strongly Disagree = 1).

The individual scores are then summed or averaged to compute an overall addiction score for each respondent. This classification helps in analyzing patterns between addiction intensity and emotional well-being. Higher addiction scores generally indicate greater dependency on social media platforms and are often associated with increased emotional exhaustion and reduced psychological balance.

An addiction score was calculated based on user responses. Points were assigned when respondents agreed or strongly agreed with addiction-related statements. Emotional exhaustion due to social media was also considered while calculating the addiction score. The addiction score is based on variables numbered 11, 14, 17 and 19 as indicated in the Table 1.

The addiction score was categorized into three levels:

- Low Addiction
- Medium Addiction
- High Addiction

a. Creation of Emotional Well-being Score

An emotional well-being score was calculated based on user responses to psychological and emotional indicators. To calculate the emotional well-being score, several related variables are included, such as:

- Emotional exhaustion due to social media
- Feeling pressured to appear perfect online
- Sleep disturbance due to usage
- Impact on productivity or academic/work responsibilities
- Mood changes after using social media
- Anxiety or stress levels related to online interactions

Instead of analyzing each variable separately (univariate analysis), multivariate analysis examines how these variables collectively contribute to overall emotional well-being. Based on the score, users were categorized into:

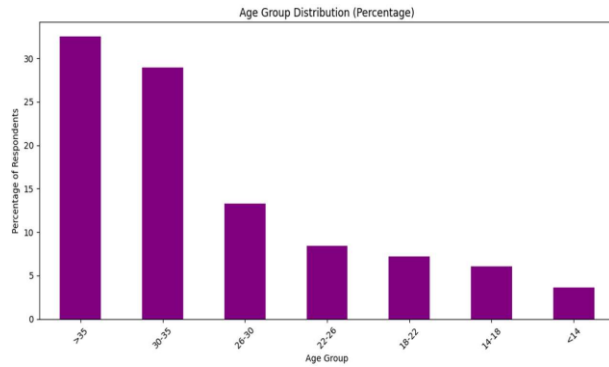


Fig. 1: Age Group Distribution

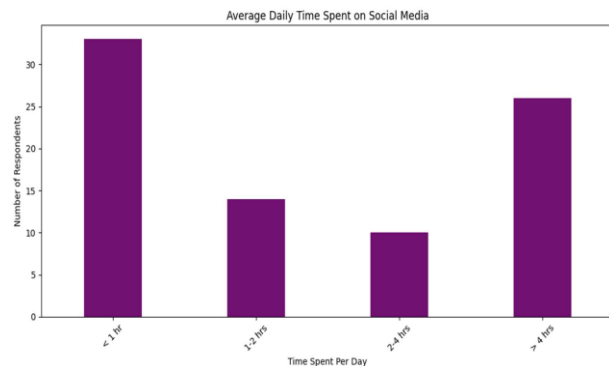


Fig. 2: Average daily time spent on social media

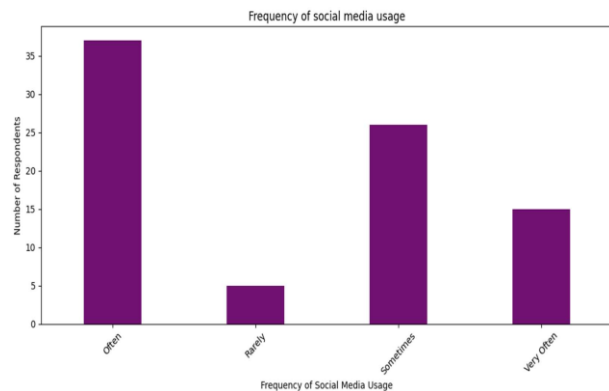


Fig. 3: Frequency of Social Media Usage

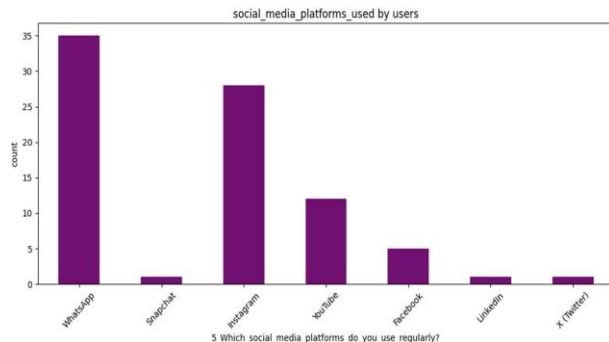


Fig. 4: Mostly Used Social Media

Emotionally_exhausted_due_to_social_media?

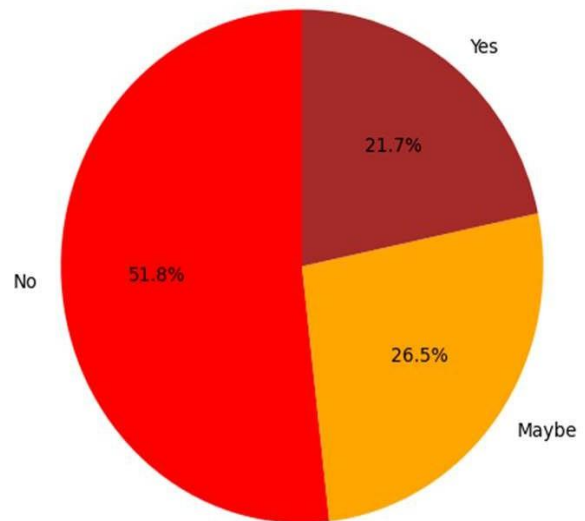


Fig. 5: Percentage of users emotionally exhausted due to social media

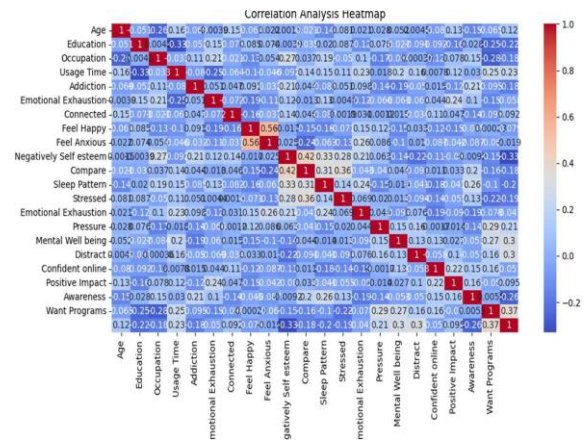


Fig. 6: Correlation Analysis Heatmap

VI. MODEL DEVELOPMENT AND CLASSIFICATION USING LOGISTIC REGRESSION

- Independent Variable (Feature): Addiction Level
- Dependent Variable (Target): Emotional Well-being

Since Logistic Regression requires numerical input, the categorical addiction levels were converted into dummy variables using one-hot encoding.

1. Model Development

The dataset was separated into training and testing datasets with an 80:20 split. Stratified sampling

ensured proportional representation of emotional well-being categories in both datasets.

A Logistic Regression model was developed using the Scikit-learn library. The model was trained using the training dataset and configured with increased iteration limits to ensure model convergence.

2. Model Evaluation

The Logistic Regression model was evaluated based on the following metrics:

3. Accuracy Score

Accuracy refers to the proportion of correct predictions made by the model. This measures the categorization model's overall effectiveness. The model accurately predicted emotional well-being for 94.12% of respondents. The high accuracy indicates that the chosen independent variables accurately explain the dependent variable, and the model performs well in classification.

4. Confusion Matrix

The confusion matrix provides a detailed comparison between actual and predicted emotional well-being categories. It helps identify classification errors and prediction accuracy for each class. The confusion matrix obtained for our data set is shown in Table 2. The model correctly predicted 12 instances of Class 1 emotional well-being. 1 instance of Class 1 was incorrectly classified as Class 2. The model correctly predicted 3 instances of Class 2 without any misclassification. The model correctly predicted 1 instance of Class 3 without any error. There were no incorrect predictions between Class 2 and Class 3.

5. Overall Interpretation:

The confusion matrix shows that the model has very strong classification ability with minimal misclassification. The majority of respondents were correctly categorized into their respective emotional well-being levels. The small number of misclassified cases indicates that the model has high reliability and predictive capability. Therefore, Logistic Regression proves to be an effective technique for predicting emotional well-being based on social media usage patterns.

6. Classification Report

The classification report provides additional evaluation metrics such as:

1. Precision- Precision refers to the proportion of correctly predicted positive observations out of all observations that the model predicted as positive. It measures how accurate the positive predictions of the model are. In the context of your project, precision indicates how many of the users predicted by the model to have emotional well-being issues due to social media usage are actually experiencing those issues.

$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$ Where:

TP (True Positives) – Cases where the model correctly predicts the positive class.

FP (False Positives) – Cases where the model incorrectly predicts the positive class.

2. Recall- Recall is a performance evaluation metric used in classification models. It measures the ability of the model to correctly identify all actual positive cases. In other words, recall indicates the proportion of actual positive observations that were correctly predicted by the model.

$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$ Where:

TP (True Positives): Cases where the model correctly predicts the positive class.

FN (False Negatives): Cases where the model incorrectly predicts a negative class even though the actual class is positive.

3. F1-score- The F1 Score is a performance evaluation metric used in classification models that combines Precision and Recall into a single measure. It represents the harmonic mean of precision and recall, providing a balanced evaluation of a model's performance, especially when there is an imbalance between classes.

$\text{F1 Score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$ Explanation

The F1 Score ranges between 0 and 1:

- 1 indicates perfect precision and recall.
- 0 indicates poor model performance.

A higher F1 Score means the model maintains a good balance between precision and recall, reducing both false positives and false negatives.

These metrics help evaluate the model's reliability in predicting emotional well-being levels. The

classification report after applying logistic regression is shown in Table 5.3.

The model achieved an overall accuracy of 94%, indicating that it correctly classified most of the respondents into their respective emotional well-being categories.

4. Class-wise Interpretation

Good Emotional Well-being - The precision value of 1.00 indicates that all respondents predicted as having good emotional well-being were correctly classified. The recall value of 0.92 shows that the model correctly identified 92% of actual good emotional well-being cases. The F1-score of

0.96 indicates strong overall classification performance for this category. The model classified 13 respondents under this category.

1. Moderate Emotional Well-being - The precision value of 0.75 indicates that 75% of respondents predicted as moderate were correctly classified. The recall value of 1.00 shows that the model successfully identified all actual moderate cases. The F1-score of 0.86 reflects good model performance for this category. The model classified 3 respondents under this category.

2. Poor Emotional Well-being - The precision value of 1.00 indicates that all predicted poor emotional well-being cases were correct. The recall value of 1.00 shows that the model identified all actual poor emotional well-being cases. The F1-score of 1.00 indicates perfect classification performance for this category. The model classified 1 respondent under this category.

3. Average Performance Measures - The Macro Average F1-score (0.94) shows that the model performs consistently across all emotional well-being categories. The Weighted Average F1-score (0.94) indicates strong overall classification performance while considering class imbalance.

7. Prediction Implementation

The trained model was further tested using new sample data to predict emotional well-being based on addiction level. The model successfully classified the emotional well-being category, demonstrating its practical applicability. The model is tested for both high and low addiction levels. It correctly classified high addiction level data into poor emotional wellbeing class and low addiction score into good emotional well being class.

The results indicate a strong relationship between social media addiction and emotional well-being. Higher addiction levels were found to be associated with lower emotional well-being levels. Logistic Regression proved to be an effective method for classification and prediction in this study.

Conclusion

This chapter demonstrated the successful implementation of Logistic Regression for predicting emotional well-being based on social media addiction. The model provides meaningful insights into behavioral patterns and helps in understanding the psychological impact of excessive social media usage. The findings can assist researchers, educators, and policymakers in designing awareness programs to promote healthy social media usage.

Table I: Variables in the Data Set

Sr. No.	Variable	Category (Scale Type)	Description
1	Age Group	Ordinal	Represents the age category of respondents, arranged in increasing order of age.
2	Gender	Nominal	Identifies the gender of respondents without any ranking or order.
3	Educational Qualification	Ordinal	Indicates the education level of respondents in an ordered manner.
4	Occupation	Nominal	Represents the professional or academic status of respondents.
5	Preferred Social Media Platform	Nominal	Identifies the most commonly

Sr. No.	Variable	Category (Scale Type)	Description
			used social media platform by respondents.
6	Average Daily Time Spent on Social Media	Ordinal	Measures the amount of time respondents spend on social media in categorized ranges.
7	Frequency of Social Media Usage	Ordinal	Shows how often respondents use social media platforms.
8	Purpose of Social Media Usage	Nominal	Identifies the main reason for social media usage such as
9	Number of Social Media Platforms Used	Ordinal	Represents the number of social media platforms actively used by respondents.
10	Checking Social Media Before Sleeping	Nominal	Indicates whether respondents use social media before going to sleep.
11	Impact of Social Media on Productivity	Likert Scale (Ordinal)	Measures respondents' perception of how social media affects their productivity.

Sr. No.	Variable	Category (Scale Type)	Description
12	Feeling Addicted to Social Media	Likert Scale (Ordinal)	Evaluates whether respondents feel addicted to social media usage.
13	Comparison with Others on Social Media	Likert Scale (Ordinal)	Measures how often respondents compare themselves with others on social media.
14	Effect of Social Media on Self-esteem	Likert Scale (Ordinal)	Examines the influence of social media on respondents' confidence and self-worth.
15	Feeling Happy While Using Social Media	Likert Scale (Ordinal)	Measures the level of happiness experienced while using social media.
16	Emotional Exhaustion Due to Social Media	Likert Scale (Ordinal)	Evaluates whether respondents feel emotionally drained due to social media usage.
17	Stress Due to Social Media	Likert Scale (Ordinal)	Measures stress levels caused by social media interactions or content.
18	Anxiety Due to Social Media	Likert Scale (Ordinal)	Examines anxiety experienced

Sr. No.	Variable	Category (Scale Type)	Description
			due to social media usage.
19	Sleep Disturbance Due to Social Media Usage	Likert Scale (Ordinal)	Measures whether social media affects respondents' sleep patterns.
20	Mood Changes After Using Social Media	Likert Scale (Ordinal)	Evaluates emotional changes after social media usage.
21	Social Media Influence on Real-life Relationships	Likert Scale (Ordinal)	Examines the effect of social media usage on personal relationships.
22	Overall Emotional Well-being Level	Ordinal	Represents the overall emotional and psychological condition of respondents.

Table II: Confusion Matrix for the Data Set

Actual / Predicted	Class 1 (Good)	Class 2 (Moderate)	Class 3 (Poor)
Class 1(Good)	12	1	0
Class 2(Moderate)	0	3	0
Class 3(Poor)	0	0	1

Table III: Output—Emotional Well-being Score

Emotional Well-being Category	Precision	Recall	F1-Score	Support (No. of Respondents)
Good	1.00	0.92	0.96	13
Moderate	0.75	1.00	0.86	3
Poor	1.00	1.00	1.00	1

Emotional Well-being Category	Precision	Recall	F1-Score	Support (No. of Respondents)
Overall Accuracy	—	—	0.94	17
Macro Average	0.92	0.97	0.94	17
Weighted Average	0.96	0.94	0.94	17

VII. FINDINGS

The findings of the study on social media usage and emotional wellbeing are as under –

Based on the descriptive analysis, the following major findings were observed:

1. Social media usage is highest among younger age groups.
2. Most respondents spend more than two hours daily on social media.
3. Social media platforms are accessed multiple times a day.
4. Entertainment and communication platforms dominate user preference.
5. A noticeable number of users experience emotional exhaustion due to social media exposure.

The dataset was separated into training and testing datasets with an 80:20 split. The logistic regression model was developed for classification and prediction based on social media usage. The Logistic Regression model was evaluated based on accuracy, precision, F1-score and confusion matrix. The model accurately predicted emotional well-being for 94.12% of respondents.

The confusion matrix shows that the model has very strong classification ability with minimal misclassification. The majority of respondents were correctly categorized into their respective emotional well-being level as shown in Table 3. The small number of misclassified cases indicates that the model has high reliability and predictive capability. Therefore, Logistic Regression proves to be an effective technique for predicting emotional well-being based on social media usage patterns.

The results indicate a strong relationship between social media addiction and emotional well-being. Higher addiction levels were found to be associated with lower emotional well-being levels. Logistic Regression proved to be an effective method for classification and prediction in this study.

VIII. CONCLUSION

The present study titled “Social Media Usage and Emotional Well-being: An Analytical Perspective” aimed to examine the relationship between social media usage patterns and the emotional well-being of individuals. The study was conducted using primary data collected through an online questionnaire and analyzed using statistical and predictive modeling techniques.

The findings of the study indicate that social media usage has a significant influence on the emotional well-being of users. The analysis revealed that factors such as time spent on social media, frequency of usage, and behavioral engagement patterns are associated with emotional conditions such as happiness, stress, anxiety, and self-esteem. The correlation and graphical analysis helped in identifying patterns and relationships between social media usage and emotional responses.

The Logistic Regression model developed in the study demonstrated strong predictive performance with high accuracy, indicating that social media usage variables are effective predictors of emotional well-being levels. The classification results showed that the majority of respondents were accurately categorized into emotional well-being levels, which confirms the reliability of the analytical model used in the research. Overall, the study highlights that while social media provides benefits such as communication, entertainment, and information sharing, excessive or uncontrolled usage may negatively affect emotional health. The research contributes to understanding behavioral patterns associated with social media usage and provides valuable insights for future studies in this area.

IX. RECOMMENDATIONS

The various recommendations based on the study are Individuals should maintain a balanced and controlled usage of social media to avoid negative emotional

effects such as stress and anxiety. Awareness programs should be conducted to educate users about the psychological impact of excessive social media usage. Educational institutions can encourage students to practice digital well-being and promote healthy online habits. Users should be encouraged to limit screen time and engage in offline activities such as physical exercise, hobbies, and social interactions. Social media platforms can introduce features that promote responsible usage, such as screen time monitoring and mental health awareness notifications. Future research can be conducted with a larger and more diverse sample size to improve generalization of results. Advanced analytical techniques such as machine learning and deep learning models can be applied in future studies for better predictive accuracy.

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