Social Media Survey Dataset: Exploring the Impact of Social Media on Personal Well-Being

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Abstract – Social media is already an essential feature of life and gradually takes some place in the everyday life of people. Regarding its impact on social life, it has earned growing interest by the society in aspects like happiness in general, mood, concentration, and sleeping. These effects are, as a result, systematically and comprehensively investigated in the research with the help of the Social Media Survey Dataset [1], which comprises cross-sectional ordinal data of different nature and several possible outcomes of the use of such platforms. The study involves the gathered data of the participants with different ages and occupations. Descriptive questions dealt with a specific content, emotions the content provokes, and probable effects on mood, the attention span, and sleep quality when consuming content. Therefore, it is on such data preprocessing steps as feature encoding and dimensionality reduction, as through the application of PCA method [2], that the data was analyzed. In order to combat the problem of class imbalance, during training the Synthetic Minority Oversampling Technique (SMOTE) was used and also stratified sampling [3]. To perform the preliminary work on the project, five machine learning models were used, and they are Logistic Regression, Support Vector Machines, Random Forest, XGBoost, and Artificial Neural Network [4]. The accuracies increased considerably after optimization (SMOTE + PCA + stratified splits), 45.8% in the case of focus quality and 70.1% in the case of sleep quality were attained using XGBoost. Even weighted F1-scores rose (e.g., 0.457 on the focus quality and 0.697 on the sleep quality), implying that these weighted F1-scores are more predictive than former baselines.

Keywords – behavioral research, digihealth, mood disorders, social media.

I. INTRODUCTION

Exploring today's interconnected society, along with the impact of social technologies on the health of people today, is an important topic of study. Presently, social media platforms retain millions of active users throughout the world [1], and these networks have significantly transformed the ways people interact, share knowledge, or have access to various materials [5]. Such platforms provide excellent environments for networking and acquiring new knowledge, but they are also present everywhere and have caused many problems [6]. With the ever-increasing digital interaction, the question of what psychological and physiological impact of constant social media use is a matter of societal concern [7].

Many emerging researchers have pointed out that multiple aspects of well-being, such as mood control, attention, and sleep, are linked to social media in various ways [6], [8]. Social media is a means for exposing one's identity and a way of finding companionship by some, while it deepens loneliness, anxiety, or depression in others [9]. The role of emotions in driving excessive use of platforms like Twitter during the COVID-19 lockdown has been particularly noted, emphasizing the nuanced ways digital technologies intersect with psychological states [21]. Moreover, factors like cyberbullying, insecurity due to comparison, and information overload add to these problems as well [10]. Likewise, constant use of the device and especially browsing at night are associated with loss of sleep and focus, and productivity [1], [8]. These effects are especially seen among high-risk groups, including adolescents and those with other illnesses ranging from anxiety to depression [11]. The problematic use of digital technologies during the pandemic further highlights how machine learning methods can provide insights into these impacts and aid in developing mitigation strategies [22].

However, the relatively recent emergence of this field has been understandably hindered by the weakness of the data sources, which are still scarce, inconsistent, and not easily categorized – this has made it rather difficult to achieve reproducible research, more inclusive systematic reviews, and even the development of evidence-based interventions [12].

As such, the Social Media Survey Dataset was developed to meet these challenges and fill current gaps in research support [13]. It also contains a vast range of variables, including social media activities, self-reported mood, cognition, and sleep diary data. When compiling such data into a single structure, this dataset helps the researcher discover many different connections that more conventional approaches would normally miss [14]. In doing so, it allows one to use machine learning techniques for establishing the relationships and forecasting the factors for the development of actionable prevention and cessation approaches targeting enhanced mental health and digital literacy [15].

This paper describes the design, construction, and pre-processing strategies used in creating the social media survey dataset. Particular attention is paid to the data accuracy, the issues of ethics, and the samples' representation of different populations. Furthermore, this paper shows a case in using the dataset by providing baseline results on the temporal analysis of mood disorders, focus quality, and sleep cycles, and Predictive Models. As this work grapples with the key concerns in social media research, it seeks to advance knowledge on psychological and behavioral effects of the digital age, in the service of guiding policies and practices that minimize the harms, while maximizing the benefits. The intent for this resource, therefore, is that it provides a groundwork upon which subsequent studies can be built, such that researchers, policymakers, and mental health practitioners can respond to pivotal questions as the digital environment continues to transform over time.

II. LITERATURE REVIEW

1. **"Revealing the Complex Relationship between Social Media Use, Social Comparison Orientation and Optimism on Health Outcomes" by Chris Gibbons & Sophie Murray-Gibbons (2022):** This paper analyzed the correlation between usage of social media, optimism, and some aspects of well-being. More than 300 adults gave an online opinion as to their use of social media, optimism, quality of sleep, mood, and well-being. They said that optimism influenced the sleep, mood, and overall well-being of the subjects significantly. However, the study used a simple random sampling technique and thus used convenience sampling; there is the possibility of nonresponse bias. The findings of the current study suggest that more research is needed to uncover the interconnections between optimism and healthy use of social media, as well as to uncover the processes assumed in the current investigation and offer additional practical suggestions for mindful use of social networks [1].
2. **"Excessive use of social media related to mental health and decreased sleep quality in students" by Vítor Cruz Rosa Pires de Souza, Alessandra Aparecida Vieira Machado et al. (2023):** The paper highlights how the use of social media, especially in college students, has led to a deterioration of mental health and sleep quality. Literature review showed increased agreement that excessive social media use, particularly in the evening, reduces sleep quality and can worsen mental and physical health affecting brain functions such as thinking, mood, learning, and behavior. The paper emphasizes healthy social media use for students and the role of families and healthcare practitioners [20].
3. **"Sleep or Scroll: The Effect of Social Media on Sleep" by Crystal Nguyen, Mary Adakama et al. (2023):** This study analyzes how social media use among adolescents affects sleep. While social media offers opportunities for self-identity and social interaction, excessive use can disrupt sleep. Lack of quality sleep is linked with high social media usage and can increase risk for mood disorders. The study emphasizes balancing offline and online activities for overall well-being [19].
4. **"The Impact of Smartphone and Social Media Use on Adolescent Sleep Quality and Mental Health during the COVID-19 Pandemic" by Young H Wa Lee, Furhut Janssen et al. (2023):** The study found higher social media use negatively affected sleep quality and increased depressive symptoms. Bringing smartphones to bed was associated with poor sleep. Authors recommend improving awareness and promoting healthy habits among youth [4].
5. **"Impact of Social Media Use on Sleep and Mental Health in Youth: A Scoping Review" by Danny J Yu, Y. Wing, Tim M H Li et al. (2024):** This review shows that social media use is linked to both positive aspects (social connection) and negative aspects (poor sleep quality, psychological issues). It calls for future research using advanced methodologies to assess long-term impacts [6].
6. **"Mediating Effect of Sleep in the Association between Social Media Use and Mental Health among French Adolescents during the COVID-19 Sanitary Crisis" by Bérard M, Manneville F et al. (2023):** This intervention study observed that increased social media use resulted in negative effects on mental health, including anxiety and depression, primarily due to disrupted sleep [18].
7. **"A Preliminary Study on the Association between Social Media at Night and Sleep Quality" by Patricia Reinheimer et al. (2022):** The study shows nocturnal social media use lowers sleep quality due to fear of missing out (FoMO) and cognitive pre-sleep arousal. This research supports interventions targeting healthier nighttime routines [14].
8. **"The Associations between Problematic Social Networking Site Use and Sleep Quality, ADHD, Depression, Anxiety and Stress" by Zaheer Hussain and Mark D. Griffiths (2021):** This paper finds higher problematic use of social networking sites strongly associated with lower sleep quality and increased ADHD, depression, anxiety, and stress [8].

9. **"Social Media-Related Nightmare: A Potential Explanation for Poor Sleep Quality and Low Affective Well-Being in the Social Media Era" by Reza Shabahang, Sohee Kim et al. (2024):** The study introduces the concept of "social media-related nightmares" and highlights its association with poor sleep quality, high anxiety, and low well-being, suggesting nightmares as a moderating factor [9].

III. DATASET CREATION METHODOLOGY

A. Data Collection

The survey was conducted online, enabling participation from diverse age groups and professional backgrounds, including students, working professionals, homemakers, and parents [1]. Key dimensions included social media usage frequency, emotional and behavioral impacts such as mood swings and anxiety, and perceived changes in sleep quality and concentration after social media use. Responses were collected through self-administered questionnaires using a five-point Likert scale. All responses were anonymous, ensuring privacy and avoiding personally identifiable information. Some of the key questions explored in the survey included:

- Social media usage patterns (frequency, platform preferences).
- Emotional and behavioral effects (e.g., mood swings, anxiety).
- Sleep quality and concentration after using social media.

Data was administered through an online self- administered questionnaires using five-point likert scale. But the responses received were anonymous and ensured this privacy and to the best of my efforts no names or email addresses were captured.

B. Data from Forms

This included an employability skills inventory that combined close ended questions, Likert scale type of questions and narrative questions to get broader perspective and comprehensive picture of the respondents' social media use and its impact or otherwise. Questions also explored behavioral indicators such as binge-watching habits, self-comparison on social media, and perceived content negativity [6], [19]. The following are the questions exactly used in the survey:

1. What is your profession? (Choose all that apply)
2. Does using social media at night make it harder or easier for you to sleep?
3. Do you notice mood swings or irritation after using social media?
4. What type of content do you watch most on social media?
5. How long do you think you spend on social media daily?
6. How long do you actually spend on social media (based on app tracking)?
7. Do you find it hard to focus after using social media? (e.g., after watching Instagram reels)
8. How often do you feel the urge to binge-watch reels?
9. When you're sad, do you notice seeing more sad or negative content on your feed?
10. What do you mainly use social media for?
11. How do you think social media has impacted your relationships or social interactions?
12. Do you often feel the time moving away really fast when you use social media?
13. How would you rate your sleep quality in general?
14. Do you wake up feeling refreshed after using social media before bed?
15. Do you feel anxious or stressed after using social media?
16. How often do you compare yourself to others on social media?
17. Have you experienced headaches or eye strain after prolonged use of social media?
18. During the past month, how often have you had trouble sleeping because you woke up in the middle of the night or early morning?
19. During the past month, how would you rate your sleep quality overall?
20. Do you use social media before bed?
21. Over the last two weeks, how often have you been bothered by feeling nervous, anxious, or on edge? (e.g., anxiety or panic attacks)
22. How often do you feel discomfort when you're not able to access your smartphone?

C. Data Cleaning and Preprocessing

To increase the credibility and feasibility of the dataset required for analysis, researchers engaged in a rigorous and efficient data pruning exercise. Below are the key steps performed:

1. **Renaming Columns:** To enhance readability and maintain consistency, lengthy or ambiguous column names were replaced with concise, clear labels. For example, "Does social media usage at night affect your sleep pattern as a difficulty or an ease?" was renamed to sleep_effect, and "How frequently do you experience the need to watch reels over and over again?" was renamed to reel_binge. This step improved interpretability and facilitated uniform analysis.
2. **Handling Missing Values:** The dataset was scanned for missing values using the .isnull().sum() function. Features with more than ***50%*** missing data were removed to maintain reliability. For the remaining features, numerical columns were imputed using the most frequent value strategy, while categorical features were imputed with the mode, implemented using the SimpleImputer class from the sklearn library.

3. **Removing Unnecessary Columns:** Redundant columns such as "*Unnamed: 33*" and *"timestamp"*, which had no analytical significance were dropped from the dataset.
4. **Encoding Categorical Data:** Before feeding the dataset into machine learning models, all categorical variables were encoded using the "*LabelEncoder*". Each unique value was mapped to an integer code and a dictionary of label encoders was maintained to allow reverse mapping and ensure interpretability.
5. **Addressing Class Imbalance with SMOTE:** To mitigate the class imbalance issue, the Synthetic Minority Oversampling Technique (SMOTE) was applied to the training folds. This oversampling technique generates synthetic samples for minority classes, ensuring balanced class representation during model training [3].
6. **Dimensionality Reduction with PCA:** Principal Component Analysis (PCA) was implemented to reduce feature dimensionality while retaining significant variance [2]. The number of principal components was selected based on the cumulative variance explained it helped in significantly reducing computational complexity and improving model performance.
7. **Final Verification:** Post-processing checks were conducted to confirm that no missing values remained and that the data was consistent and ready for "*Exploratory Data Analysis (EDA)*" and predictive modeling.

D. Exploratory Data Analysis (EDA)

A comprehensive exploratory data analysis was performed to understand data distribution and identify patterns that influence predictive modeling. The analysis included visualizing the distribution of target variables, correlations among features, and feature-level behavior.

A. Target Variable Distribution

The target variables—Mood Disorder, Focus Quality, and Sleep Quality—were analyzed to assess class distribution. Figure **1** shows the proportion of each class within these variables. While Mood Disorder and Focus Quality exhibit relatively balanced distributions, Sleep Quality demonstrates a noticeable skew towards higher-quality ratings. This imbalance was addressed using SMOTE (Synthetic Minority Oversampling Technique) during preprocessing to ensure uniform representation across classes.

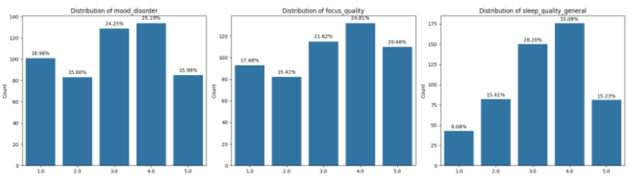

Figure 1. Distribution of target variables: (a) Mood Disorder, (b) Focus Quality, and (c) Sleep Quality.

B. Correlation Analysis

To examine relationships among numerical features, a correlation heatmap was generated. Strong correlations between some behavioral features indicate potential multicollinearity, which justified the use of PCA for dimensionality reduction.

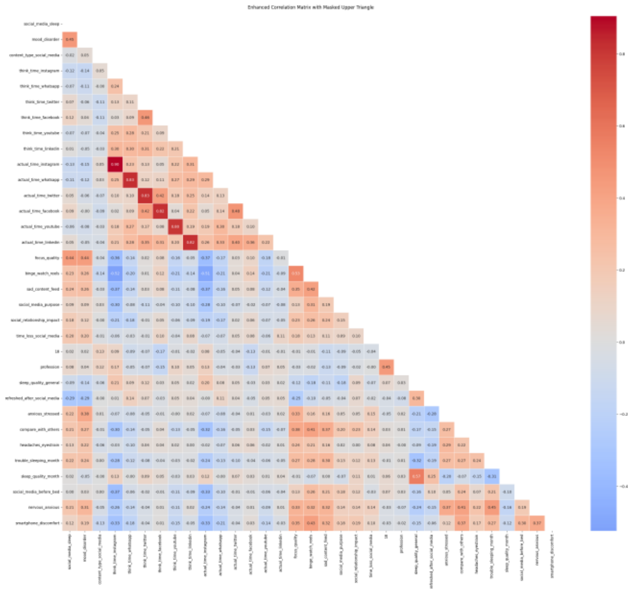

Figure 2. Correlation heatmap illustrating pairwise correlations among numerical features.

C. Scatter Plot Analysis

Scatter plots were plotted to assess trends between behavioral indicators and focus quality. These visualizations revealed subtle, non-linear relationships, supporting the use of advanced machine learning models over simple linear ones.

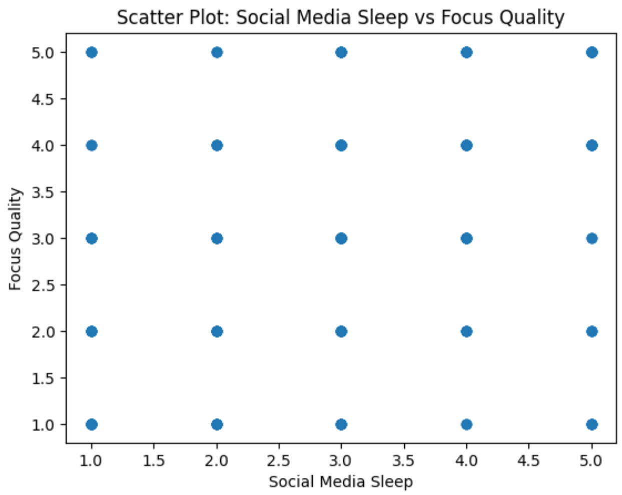

Figure 3. Scatter plot showing the relationship between social media usage before bed and focus quality.

D. Feature Distribution

Histograms for key behavioral features were plotted to analyze frequency distribution. These visualizations highlight skewed distributions, which informed the application of normalization during preprocessing.

Figure 4. Histograms showing frequency distribution of selected behavioral features.

E. Maintaining Parity

To avoid response bias, balanced sampling was ensured by monitoring demographic response patterns and adjusting promotional strategies for proportionality [6]. Researchers also Skate the promotion method to correct disproportional response. A special effort was made in wording the questions to not bias the respondents' answers.

F. Evaluation

Key areas of investigation include:

1. The shift of mood due to the exposure of content.
2. Night use of social networks leads to several sleeping disorders.
3. Effects on focus and productivity after the use of social media.

F. Flowchart

Following is the diagrammatical representation of the data preparation methodology:

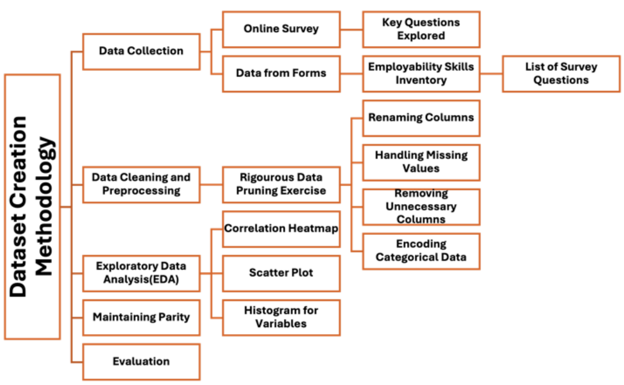

Figure 5. Flowchart of the methodology

IV. DATASET

The sample includes 532 respondents, who answered questions about the use of social networks, the quality of sleep, and mood and health consequences [1]. The dataset consists of 32 features that concern the professional experience, the tendency of social media utilization, the rates of emotional and physical behavior, and the quality of the night's sleep.

A. Descriptive Statistics

- **Participant Count:** 532
- **Total No. of columns:** 33
- **Social Media Usage:** Average time for the average number of visiting social sites to consume content is 20.83 (SD = 13.17 and range between 0 and 58).
- **Sleep Quality:** The average sleep quality as well as the overnight self-report is 3.32 (std: 1.14; range: 1–5).
- **Mood Disorders:** Index: mean = 3.06 (std dev: 1.35; range: 1–5); The results suggest moderate influences on various aspects of working life.

B. Dataset

The dataset can be accessed via:

1. https://www.kaggle.com/datasets/deveshattri/social-media-usage-and-mental-health-dataset
   or,
2. https://drive.google.com/file/d/1GBBCITRN6Fb6VbhRDyEH_4B3aVEXwVTb/view?usp=sharing

V. APPLICATIONS

This dataset has multiple applications across domains:

1. **Behavioral Research:** Understanding lifestyle impact on psychological well-being and mental health [6].
2. **Policy-making:** Formulating evidence-based recommendations for healthy social media practices [15].
3. **Machine Learning:** Training predictive models to assess risks of poor mental health based on digital habits [3].

VI. STATISTICAL ANALYSIS

To assess whether the observed associations between social media usage patterns and outcomes such as **mood disorder, focus quality, and sleep quality** were statistically significant, hypothesis testing was performed using **Chi-square (χ^2) tests** for categorical variables and **One-way ANOVA** for continuous variables [16].

A. Mood Disorder

Features such as **social_media_sleep**, **anxious_stressed**, and **nervous_anxious** showed strong associations with mood disorder categories (p-values < 0.001). For example:

- **social_media_sleep**: ANOVA statistic = 34.92, $p < 0.001$
- **anxious_stressed**: χ^2 statistic = 85.03, $p < 0.001$

Other notable features include **binge_watch_reels**, **compare_with_others** and **headaches_eyestrain**.

B. Focus Quality

Significant relationships were observed for variables like:

- **binge_watch_reels**: ANOVA statistic = 51.02, $p < 0.001$
- **social_media_sleep**: $p < 0.001$
- **think_time_instagram**: χ^2 statistic = 105.61, $p < 0.001$

Time-based features such as **actual_time_instagram** and behavioral indicators like **time_loss_social_media** were also significant predictors.

C. Sleep Quality

The feature **sleep_quality_month** had the strongest significance for predicting sleep quality (ANOVA statistic = 89.12, $p < 0.001$). Other strongly associated variables include:

- **refreshed_after_social_media**
- **trouble_sleeping_month**
- **social_media_before_bed**

Table IV summarizes selected significant variables ($p < 0.05$) across the three prediction tasks.

TABLE I: STATISTICALLY SIGNIFICANT FEATURES ($p < 0.05$)

Task	Key Features (Significant)
Mood Disorder	social_media_sleep, anxious_stressed, nervous_anxious, binge_watch_reels, sad_content_feed
Focus Quality	binge_watch_reels, social_media_sleep, think_time_instagram, actual_time_instagram, time_loss_social_media
Sleep Quality	sleep_quality_month, trouble_sleeping_month, social_media_before_bed, refreshed_after_social_media

Visual Representation of Feature Significance: Figures below illustrate the top 20 features ranked by their p-values for each task, with a red dashed line marking the 0.05 significance threshold.

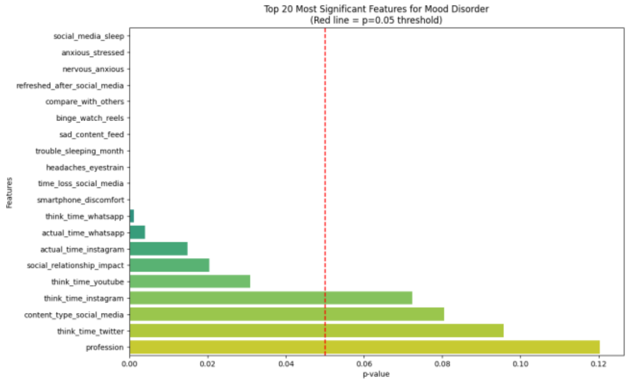

Figure 6: Top 20 most significant features influencing Mood Disorder classification (p-value ranking).

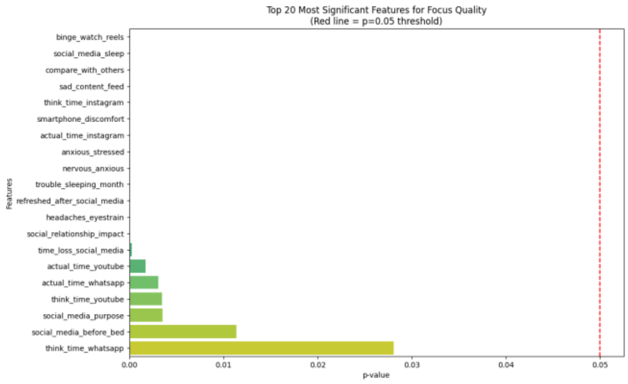

Figure 7: Top 20 most significant features influencing Focus Quality classification (p-value ranking)

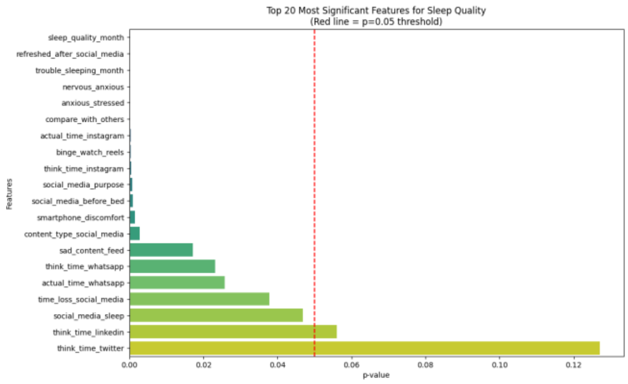

Figure 8: Top 20 most significant features influencing Sleep Quality classification (p-value ranking).

VII. BASELINE PERFORMANCE

Baseline performance metrics for **mood disorder, focus quality, and sleep cycle classification** were computed to establish a reference point for evaluating more complex models [17]. Spoken and written baseline responses for performance metrics used to classified mood disorders, focus quality, and sleep cycle are given below. It is critical to set a basic standard to compare with to, so that the efficacy of more complex models can be analyzed. It offers a benchmark for assessing changes in the predictive accuracy and for recognizing potential issues as well as for orienting prospective investigation.

TABLE II. MOOD DISORDER CLASSIFICATION

Classifier	Accuracy	Precision	Recall	F1	AUC
Random Forest	0.346	0.338	0.346	0.339	0.691
Logistic Regression	0.308	0.299	0.308	0.296	0.660
XGBoost	0.308	0.314	0.308	0.311	0.620

Logistic regression, naïve bayes, KNN, and XGBoost classifiers were used for mood disorder categories' prediction. The overall highest accuracy of **30.10%** was obtained from the technique known as logistic regression when making the predictions which suggested just how difficult it was to work with this dataset with its severely imbalanced classes. These models mainly relied on simple statistical correlations and the spread assumptions, which might not fully describe the required trends in the data, including several sub patterns.

TABLE III. FOCUS QUALITY CLASSIFICATION

Classifier	Accuracy	Precision	Recall	F1	AUC
XGBoost	0.458	0.466	0.458	0.457	0.731
Random Forest	0.402	0.403	0.402	0.400	0.742
Logistic Regression	0.280	0.281	0.280	0.276	0.731

This task extended on the more accomplished models such as the Artificial Neural Networks (ANN's) and the Support Vector Machines (SVM's). ANN's presented the highest accuracy of approximately **40.78%** exploiting their capacity to model complex dependencies. The kernel based SVM classifier achieved a total accuracy of **39.81%** proving that this classifier is effective in working with large feature space data.

TABLE IV. SLEEP CYCLE CLASSIFICATION

Classifier	Accuracy	Precision	Recall	F1	AUC
XGBoost	0.701	0.695	0.701	0.697	0.786
Random Forest	0.682	0.671	0.682	0.672	0.792
Logistic Regression	0.495	0.569	0.495	0.508	0.682

The best accuracy for sleep cycles classification was obtained by Logistic Regression with **59.26%**, while Random Forest gave **58.02%** which also indicated that linear and ensemble methods should be used. ANN and XGBoost had equal accuracy of **55.56%** and therefore had the capabilities to model other patterns if properly optimized. These are useful results for comparing to state-of-the-art models and reveal the dataset's difficulties for prediction.

VII. COMPARISON WITH THE EXISTING WORK

This research belongs to the widely discussed domain examining the multifaceted connection between **social networking site usage and subjective well-being** [1], [6]. While numerous studies have explored relationships between social media use and mental health, the primary contribution of this research lies in its **unique dataset design and methodology**.

Our findings on the detrimental effects of nighttime social media use on sleep quality align with previous studies, including Nguyen et al. (2023), Lee et al. (2023), and Reinheimer et al. (2022), which examined the mediating role of **pre-sleep cognitive arousal and FoMO** [14], [19]. Similarly, the observed associations between mood swings, anxiety, and stress corroborate prior findings by Hussain and Griffiths (2021) and Shrestha & Adhikari (2024), which identified psychological risks linked to problematic social media use [8], [9]. These alignments validate the reliability of the patterns captured in our dataset.

Furthermore, our results echo the observations of Bérard et al. (2023) on how **sleep mediates the relationship between social media use and mental health during the COVID-19 crisis** [18]. However, our study advances this discourse by offering **cross-sectional data from a broader participant base across age and occupation groups**, allowing for a more inclusive representation of social media effects at different life stages.

Unlike previous work that primarily measured **time spent on social media**, this study incorporated **content-related questions** (e.g., content type and emotional triggers) and self-reported versus actual time metrics. These granular variables facilitate nuanced analyses of how **specific content categories and emotional engagement** drive changes in well-being indicators, rather than focusing solely on usage duration.

Despite moderate baseline accuracies for mood and focus predictions, the improved performance of optimized models (e.g., XGBoost achieving 70.1% accuracy for sleep cycle prediction) demonstrates the dataset's potential as a **foundation for advanced modeling and intervention design** [16]. Future research should explore:

- The impact of **content categories** on well-being outcomes.
- **Longitudinal studies** comparing behavioral changes over time.
- Development of **behavioral interventions** to encourage healthy digital habits.

VIII. CONCLUSION

This study underscores the complex association between **social media usage and psychological well-being**, illustrating how online behaviors influence mental health, stress, and happiness [3], [6]. While excessive use fosters anxiety, reduced focus, and lower well-being, purposeful engagement—such as in educational or professional communities—can offer positive benefits [5].

Key findings include:

- Identification of behavioral markers (e.g., binge-watching reels, late-night usage) associated with **poor sleep quality and mood fluctuations**.
- Evidence that **machine learning models** can predict well-being indicators from digital behavior patterns. Logistic Regression and Random Forest provided strong baselines, while **XGBoost achieved superior performance**, particularly for sleep cycle prediction (Accuracy = 70.1%, F1 = 0.697) and focus quality (F1 = 0.457).

These results emphasize the role of **predictive analytics** in building scalable tools for **real-time monitoring** and **digital wellness interventions**. Moreover, the study reinforces the importance of **moderation and quality-focused social media use**. Insights derived from this research can guide **policy-making**, educational programs, and platform-level interventions aimed at fostering healthier digital environments [15].

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