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SOCIAL MEDIA USAGE PATTERNS AND EMOTIONAL WELL-BEING: A CROSS-PLATFORM ANALYSIS OF DIGITAL HUMAN BEHAVIOR

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Abstract

Culture is not the sole determinant of human prejudice and democratic quality; it is a product of interactions among ecological pressures, developmental conditions, and institutional environments. This study examines these dynamics from a cross-national social–ecologiThis study examines the relationship between social media usage patterns and emotional well-being through a cross-platform analytical perspective. It seeks to learn the effects of various aspects of digital interactions on how users emotionally experience them. The research design used was a quantitative, cross-sectional study that relied on a secondary dataset that was acquired through Kaggle. A total of 1000 observations in the dataset were pre-processed to yield 924 valid cases. The analysis of the study was done with Python and included descriptive statistics, correlation, and classification modeling to analyze the relationships between usage behaviors and prevailing emotional states. The findings show that there is high social media usage, and the Instagram platform has been identified as the most widely used. Emotional outcomes were diverse, with happiness and neutrality being the most prevalent, alongside notable levels of anxiety and sadness. Strong positive correlations were observed between usage intensity and engagement metrics. The classification model demonstrated moderate predictive capability uggesting that behavioral patterns can partially explain emotional outcomes. The findings highlight the complex and dual nature of social media, acting as both a source of social connection and emotional strain. The study contributes to understanding digital human behavior and offers insights for developing strategies to promote health healthier online engagement.

Keywords: Social media usage, emotional well-being, digital behavior, cross-platform analysis, social interaction, online engagement, user behavior, digital communication

1. Introduction

The fast growth of social media platforms has essentially altered the manner in which people interact, socialize, and create their social worlds. In the last ten years, social networks like Instagram, Twitter, Facebook, and new messaging apps have become a part of everyday existence, not only forming communication trends but also determining psychological experiences and emotional health. The environments of social media allow their users to express and be socially validated, engaging with communities; nevertheless, they create the problem of comparison, information overload, and digital fatigue. (Burke & Kraut, 2016; Keles et al., 2020). This has led to the fact that the connection between the pattern of social media use and emotional well-being has become a very important subject of investigation in modern social and behavioral studies.

Behaviorally, the use of social media can be perceived as an intensity and engagement. Usage intensity is the amount of time people spend on digital platforms, whereas engagement includes such activities as posting content, communicating with other users, and reacting to feedback in the shape of likes and comments. These dimensions are tightly connected with the emotional experience of the users, as the higher the level of engagement, the more exposure to social feedback and online interactions the user may have (Burke et al., 2010; Verduyn et al., 2017). Although positive interaction may increase a sense of belonging and happiness, negative events like social comparison or lack of interaction may also lead to anxiety, loneliness, and reduced well-being (Appel et al., 2016).

The connection between the use of social media and emotional well-being is ambiguous and inconsistent. According to some studies, social media can also have positive consequences as it allows users to connect socially and provide emotional support, especially to younger audiences (Best et al., 2014). On the contrary, the other studies emphasize adverse consequences of excessive use, such as a higher amount of stress, anxiety, and depressive symptoms (Primack et al., 2017; Twenge & Campbell, 2018). These contradictory results point to the fact that the effects of social media do not happen across the board, but rather, it is the ways that people utilize these platforms and the situations where they interact. Specifically, platform differences could be an important factor, with each platform being characterized by different affordances, communication patterns, and social conventions (Chou & Edge, 2012; Ellison et al., 2007).

Digital platforms are not similar in the interactions that they provide, as well as in their functional capabilities. As an example, the image-based communication and social comparison through the visually oriented platforms like Instagram tends to be more than the platform like LinkedIn, which is oriented on professional identity and networking. Messaging applications like WhatsApp and Telegram are mostly applied in the interpersonal communication domain with more personal and smaller networks. These differences indicate that the emotional consequences can be different in relation to the context of the platform, which is why it is essential to consider a cross-platform analytical perspective (Valkenburg et al., 2022). These differences are crucial to comprehending digital behavior and its psychological consequences in a more complex way.

One more significant dimension to examine social media and well-being is the place of emotional expression and classification. Continuous psychological scales are commonly used to measure emotional well-being, but in online contexts, emotions are commonly represented and interpreted in discrete form, e.g., as happiness, sadness, anxiety, or anger. This nominal representation is especially suitable when it comes to data-driven studies about online behavior, since this is the manner in which users perceive and express feelings over the Internet (Lazarus, 1991). The study of dominant emotional states in terms of usage patterns will enable the researchers to obtain information about the behavioral engagement in relation to various emotional experiences.

Although there is an increasing amount of literature on social media and well-being, there are still a number of gaps. The current studies have largely been dedicated to the single-platform analysis or self-reported measures of usage, which might not be as comprehensive as the complexity of digital behavior across multiple platforms. Additionally, most studies base their evaluations of well-being on subjective judgments, not behavioral signs, which hinders the possibility of developing empirical correlations between engagement measures and emotional outcomes (Orben & Przybylski, 2019). Absence of research that combines various dimensions of engagement, i.e., posts, likes, comments, and messaging into a single analytical structure is also lacking. Such constraints reveal the necessity of studies that use multivariable and structured data to study the interaction between social media behavior and emotional condition in various digital situations.

In response to these gaps, the present study aims to provide a comprehensive analysis of social media usage patterns and their association with emotional well-being using a cross-platform approach. Specifically, the study seeks to examine how different dimensions of social media engagement, including usage time and interaction metrics, relate to users' dominant emotional states. By leveraging a secondary dataset containing behavioral and emotional variables, the research adopts a data-driven methodology to explore these relationships. The primary objectives of the study are to (1) analyze the distribution of social media usage across platforms, (2) examine the relationship between usage intensity and engagement metrics, and (3) assess how these behavioral factors are associated with different emotional outcomes. Through this approach, the study contributes to a deeper understanding of digital human behavior and offers insights into the complex interplay between technology use and emotional well-being.

2. Methodology

2.1 Research Design

The current research assumes a quantitative, cross-sectional research design with the secondary data analysis method to explore the connection between the patterns of social media usage and emotional well-being. The cross-sectional design enables the study of behavioral and emotional attributes at a particular time, which helps to determine the patterns and associations without creating any causal correlations. The research work is based on a positivist paradigm, which is concerned with measuring and statistically analyzing measurable digital activities. The study will use organized numerical and categorical information to produce empirical evidence on the impact of social media use on the emotional experiences of users in various online platforms.

2.2 Data Source

The dataset used in this study is a secondary dataset obtained from Kaggle, titled "Social Media Usage and Emotional Well-Being Dataset." The data set was originally a set of 1000 observations and 10 variables with information at the individual level about social media behavior and emotional states. After cleaning and preprocessing of the data, 924 valid observations were left to analyze (Bulut, 2024).

The variables that will be included in the dataset are: User ID, Age, Gender, Platform, Time spent on the platform daily (minutes), Number of posts made each day, Number of likes received each day, Number of comments received each day, Number of messages sent each day, and Dominant Emotion. The variables represent a variety of aspects of user interaction in different social media, and the data is suitable for studying behavior trends and their correlations with emotional results. This dataset is publicly accessible and anonymized and includes no personally identifiable data, thus complying with the ethical norms of research.

2.3 Variables and Measurement

The research operationalizes the patterns of social media use in terms of quantitative measures of intensity and engagement of use. The length of time spent in a digital environment every day, in minutes, can be used as a measure of exposure. The engagement-related behaviors are gauged by the number of posts made daily, likes obtained daily, comments made daily, and messages sent daily, which capture various types of interaction in social media platforms.

Platform is considered a categorical variable, as it is the unique digital environment and allows cross-platform comparisons. The operationalization of emotional well-being is based on the variable Dominant Emotion, which classifies users into specific emotional conditions: happy, anxious, sad, bored, angry, and neutral. This method is an expression of an outcome-based expression of emotional experience, as opposed to a continuous psychological scale.

Control variables, such as age and gender, are included to take into consideration any possible differences in behavior and emotional outcomes among various user groups. The measurement strategy is based on observed dataset values, and this enables quantitative analysis of the data to be carried out directly while still being interpretable.

2.4 Data Preprocessing

The data was preprocessed systematically to guarantee the data quality, consistency, and reliability before the analysis. The first check revealed some slight problems, such as the absence of values, inconsistencies in the categories' designations, and even possible duplicate values. The following problems were mitigated in the process of data cleaning: incomplete or invalid records were removed, duplication was removed, and categorical variables (Gender, Platform, and Dominant Emotion) were standardized.

The User ID variable was only used to identify the user and was not a part of the analytical modeling. Continuous variables, such as usage hours and interaction rates, were checked for outliers and translated to proper numerical forms to make them analytically accurate. All non-numeric data in these variables were coerced into valid formats or eliminated as needed.

After preprocessing, the dataset was organized into a clean and analysis-ready format, leaving 924 valid observations. All the subsequent statistical analyses were performed using this cleaned dataset.

2.5 Analytical Tools and Procedure

Python was used to analyze the data, and this is an efficient tool to manipulate, visualize, and model the data. The main libraries used are pandas, which is used to handle data, NumPy, which is used to perform numerical calculations, Matplotlib and seaborn, which are used to visualize data, and Scikit-learn, which is used to predict.

The analysis process started with exploratory data analysis in order to gain insight into the distribution and the nature of the variables. Patterns in platform use, emotional distribution, and the differences in behavior among user groups were visualized using visualization. To summarize how the data were distributed in terms of central tendencies and variability, descriptive statistics were created.

Correlation analysis was then done to test how variables of social media usage correlate with engagement metrics. Lastly, a classification modeling method was used to forecast predominant emotional states using behavioral signals. The modeling process involved data division, scaling of features, model training, and performance evaluation using suitable measures. The results were validated and robust since the analytical process was an iterative process.

2.6 Statistical Techniques

The research uses descriptive and inferential statistics to answer the research questions. The dataset is summarized by using descriptive statistics that can tell about the demographic features of the data, patterns of usage, and distributions of emotions.

The correlation analysis is performed to assess the strength and direction of the relationship between numerical variables, in particular, between the usage intensity and engagement measures. To increase the interpretability of these relationships, correlation matrices are used to visualize them.

In predictive analysis, the classification methods are applied to analyze the effect of behavioral variables on the emotional outcomes. The classification model allows recognizing patterns that differentiate between the various emotional states, depending on user behavior. Confusion matrices and associated performance indicators assess model performance and give an understanding of the accuracy and reliability of predictions.

A combination of these statistical methods will provide a holistic examination of descriptive trends as well as predictive correlations in the data set.

2.7 Ethical Considerations

The research follows the accepted ethics of research on secondary data. The dataset is publicly available and anonymized, and no personally identifiable data is revealed. Since the study is not based on direct contact with human subjects, there are no problems associated with informed consent and the risk of harm to the subjects.

The information is employed on an academic basis, and proper reference to the source is made. Further, caution is exercised to ensure findings are not misinterpreted or overgeneralized, especially in the context of secondary datasets that are limited. The paper is focused on responsible data management, openness of the approach, and honesty in presenting findings.

3. Results

3.1 Descriptive Statistics

Table 1 provides the descriptive statistics of the most important numerical variables. After preprocessing, there are 924 valid observations in the dataset. The mean age of the respondents is 27.5 years (SD = 3.94), meaning that the sample is predominantly made up of young adults. The average time spent on social media per day is 96.31 minutes (SD = 39.23), which indicates a significant time spent on digital platforms.

The variables related to engagement are moderately active. The average number of posts made by users is 3.35 times per day, the average number of likes is 40.25, the average number of comments is 15.73, and the average number of messages sent is 22.6. The broad distribution of these variables (e.g., likes between 5 and 110) implies the variability of the levels of user engagement, as there is a difference in the digital behavior of people.

Table 1. Descriptive Statistics of Key Variables

Variable	Mean	SD	Min	Max
Age	27.50	3.94	21	35
Daily Usage Time (minutes)	96.31	39.23	40	200
Posts per Day	3.35	1.94	1	8
Likes Received per Day	40.25	26.80	5	110
Comments Received per Day	15.73	8.93	2	40
Messages Sent per Day	22.60	8.63	8	50

3.2 Demographic and Platform Distribution

The gender representation of Table 2 demonstrates a relatively equal sample, where females (37.23%) outnumber males (35.93%) slightly, whereas non-binary participants represent a significant percentage (26.84%). This variety increases the representativeness of the dataset in the representation of diverse user experiences.

Table 2. Gender Distribution

Gender	Frequency	Percentage
Female	344	37.23%
Male	332	35.93%
Non-Binary	248	26.84%

Table 3 and Figure 1 show the distribution of users over the platforms. Instagram is the most popular tool (25.54%), then Twitter (20.35) and Facebook (19.26). LinkedIn covers 12.77% of the user base, with WhatsApp, Telegram, and Snapchat occupying smaller yet equal shares (7.36%). These results show that highly visual and highly interactive platforms are the most dominant platforms in user interactions, which is a current trend in digital communication.

Table 3. Platform Distribution

Platform	Frequency	Percentage
Instagram	236	25.54%
Twitter	188	20.35%
Facebook	178	19.26%
LinkedIn	118	12.77%
WhatsApp	68	7.36%
Telegram	68	7.36%
Snapchat	68	7.36%

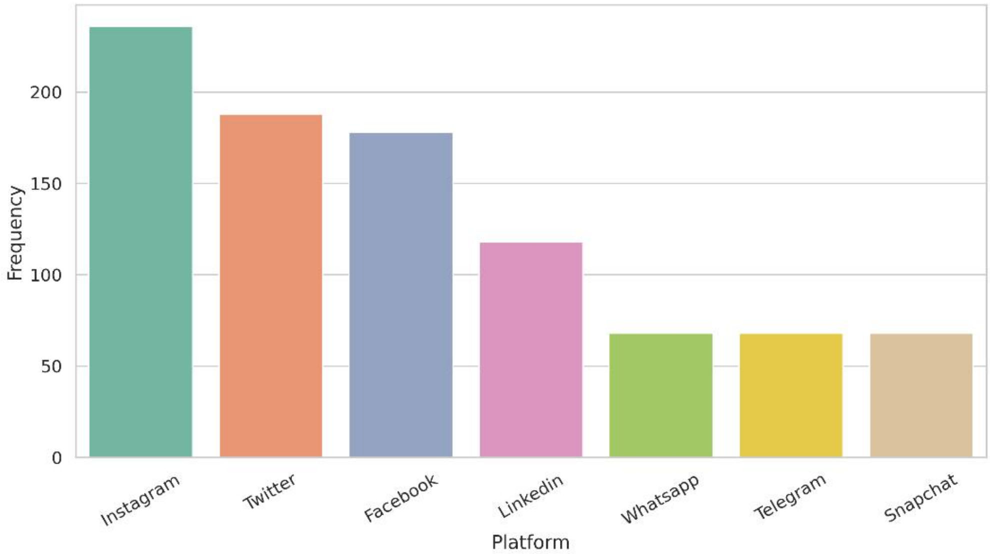

Figure 1. Distribution of Users Across Social Media Platforms

3.3 Distribution of Emotional Well-Being

Table 4 and Figure 2 provide the distribution of the dominant emotional states. The most frequent emotional states are happiness (20.13%) and neutrality (19.91), then anxiety (16.88%) and sadness (15.80%). Boredom (14.07%) and anger (13.20%) are comparatively less frequent but still significant.

This distribution indicates that, although positive emotional experiences are a bit more common, a significant share of users express negative or neutral emotional states, indicating the multifaceted emotional environment regarding social media usage.

Table 4. Distribution of Dominant Emotions

Emotion	**Frequency**	**Percentage**
Happiness	186	20.13%
Neutral	184	19.91%
Anxiety	156	16.88%
Sadness	146	15.80%
Boredom	130	14.07%
Anger	122	13.20%

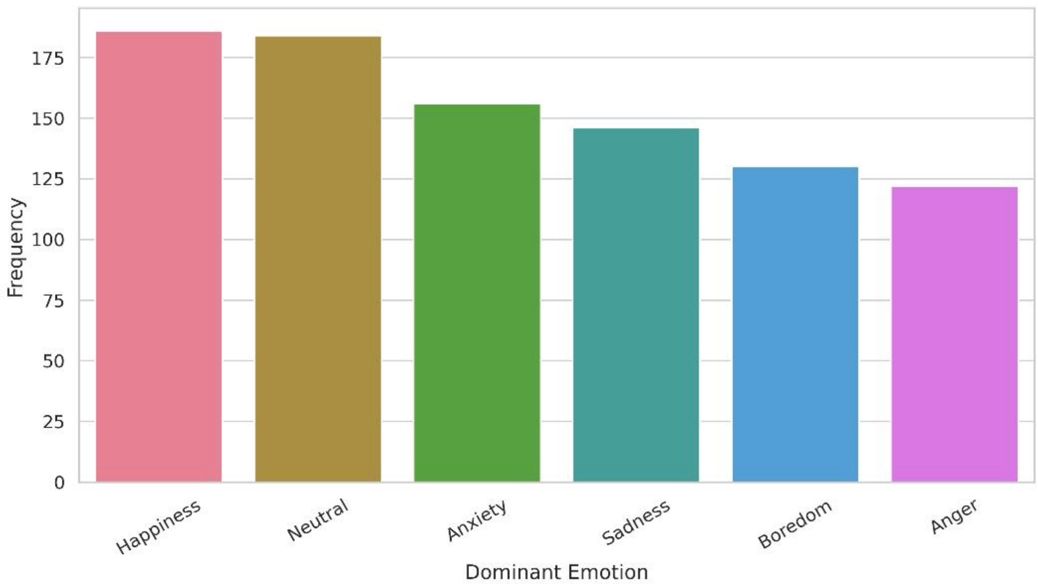

Figure 2. Distribution of Dominant Emotions

3.4 Platform-Based Usage Patterns

Figure 3 shows the difference in the time of daily use in the different platforms. Instagram users have the highest median usage time and a wider interquartile range, which means that there is high engagement and variation in usage between individual users. Social sites like LinkedIn have relatively less frequent usage as they are more professional and offer less frequent usage.

WhatsApp and Snapchat exhibit a middle-level usage, indicating the use of the platforms as communication-based networks and not content-driven platforms. These variations underscore the platform attribute and its effect on user behavior and the degree of engagement.

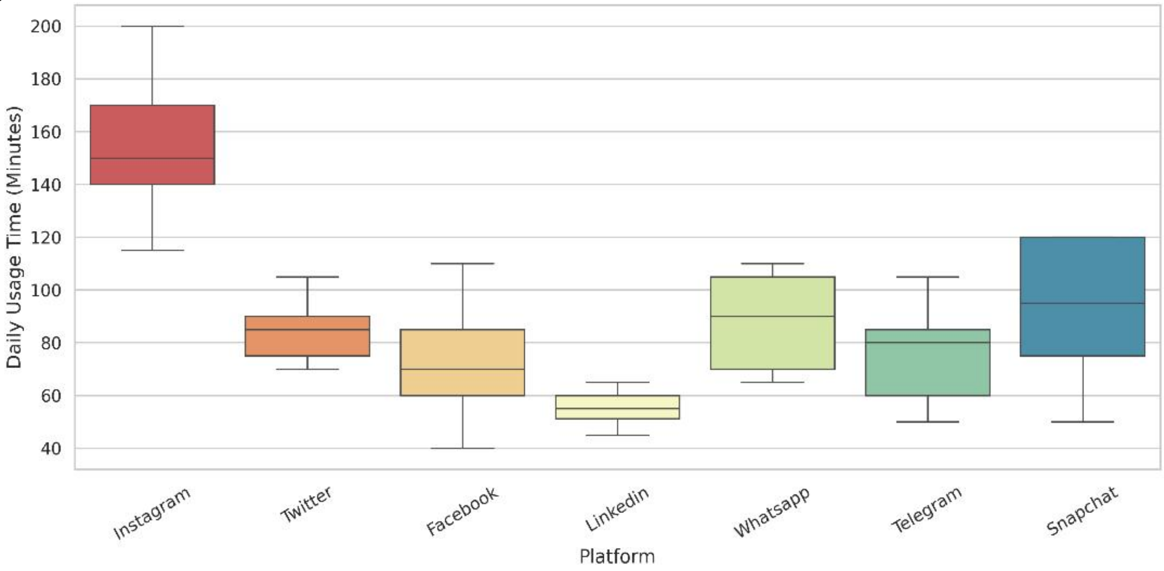

Figure 3. Daily Social Media Usage Time Across Platforms

3.5 Correlation Analysis

The correlation map in Figure 4 indicates that there are strong positive correlations between the behavioral variables. The posts per day (r = 0.89), likes received (r = 0.94), comments received (r = 0.90), and messages sent (r = 0.92) have a high correlation with daily usage time. Likewise, the number of posts per day is significantly correlated with likes (r = 0.92) and comments (r = 0.92).

These results show that the more time one spends on social media, the more the user engagement is strongly related in several aspects. Conversely, age is weakly related to all other variables (r < 0.11), indicating that the patterns of behaviors are not significantly different among age groups in the sample.

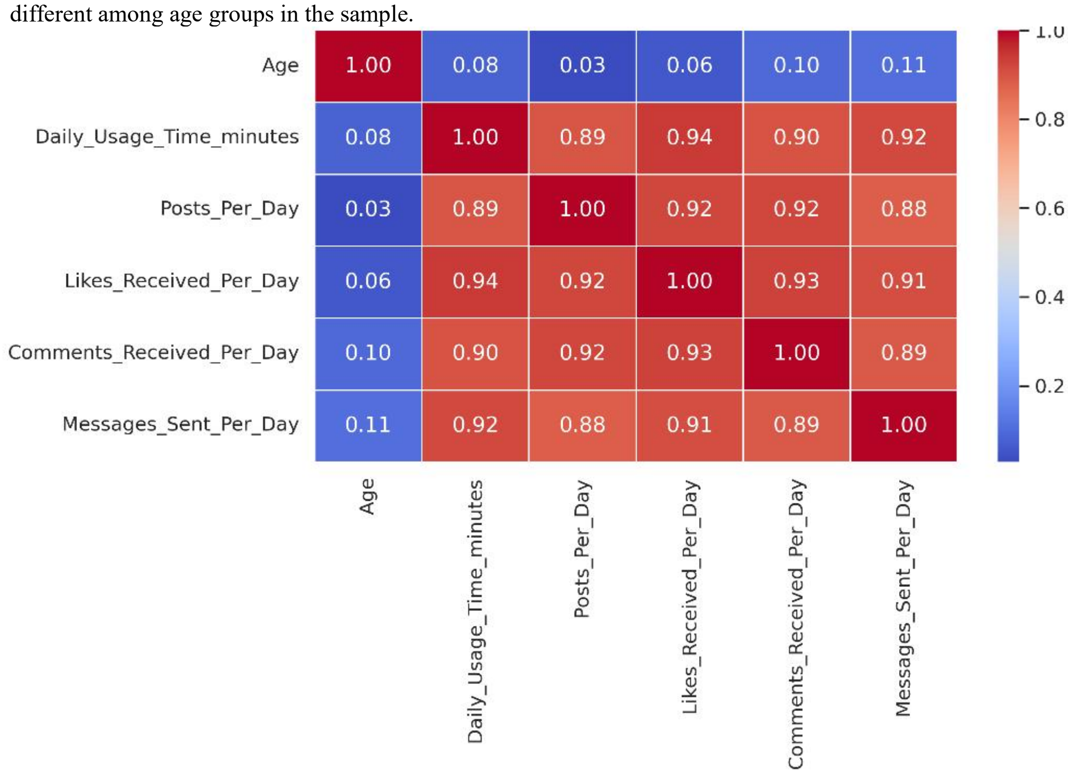

Figure 4. Correlation Matrix of Numerical Variables

3.6 Predictive Model Performance

Figure 5 shows the performance of the classification model that is used to predict dominant emotion. The confusion matrix shows that the model does not do so badly in forecasting some emotional states like happiness and boredom, as the number of correct classes increases along the diagonal.

Nonetheless, there is a certain misplacement among conceptually similar states of emotions, like anxiety and sadness, or neutral and anxiety. This indicates that there is overlap in behavioral patterns relevant to these emotions, which are even harder to differentiate using just usage metrics.
Generally, the model represents a moderate predictive power, which means that although social media behavior can offer valuable information on the emotional states, it might not be sufficient to reflect the complexity of human emotional experience.

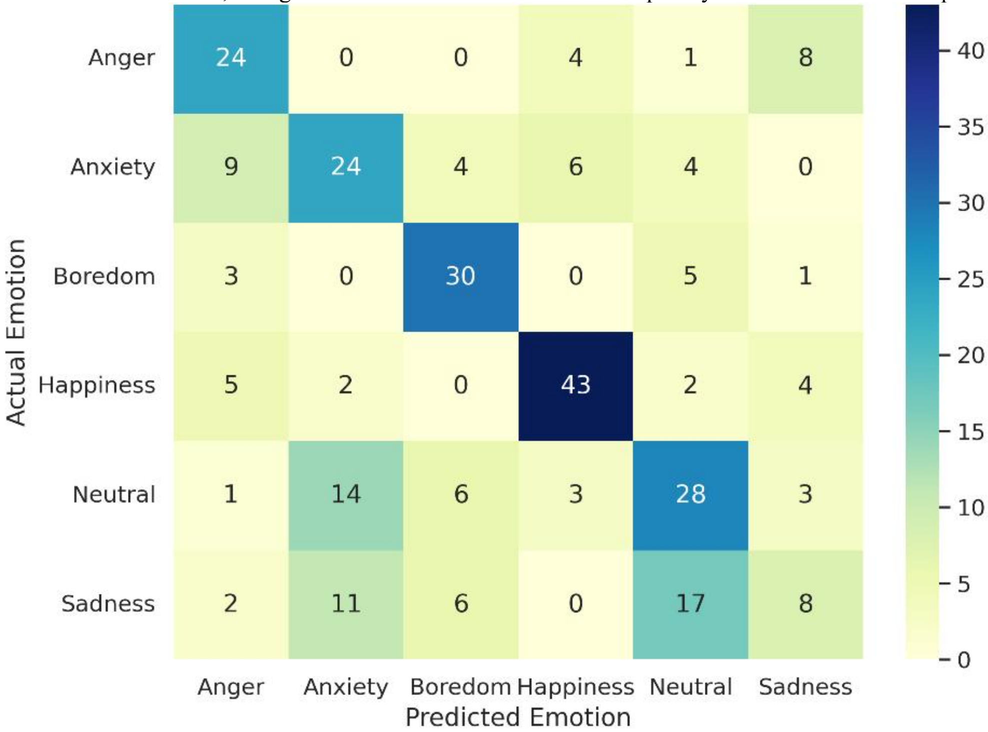

Figure 5. Confusion Matrix for Emotion Prediction

4. Discussion

The current research aimed at investigating the interaction between social media consumption patterns and emotional well-being in relation to a cross-platform analysis perspective. The results indicate that the use of social media is not only common but also complex, as participants display different degrees of interaction on different platforms and have a mixed field of emotional effects. The findings are beneficial to the emerging body of research on digital human behavior as they present empirical data associating behavioral engagement measures with categorical affective states, thus offering a subtle insight into the influence of digital environments on psychological experiences.
The first and one of the most significant study findings is the positive relationship between the intensity of use and the engagement measures, as indicated in the correlation analysis. An increase in the daily time of use correlated with more posting, liking, commenting, and messaging activities. This is consistent with the theoretical approach of Uses and Gratifications Theory, which assumes that people actively participate in media platforms in order to satisfy particular psychological and social needs, including entertainment, socialization, and expressing themselves (Katz et al., 1973). The noted behavior trends indicate that the more time users spend on social media, the more they are likely to demand gratification by engaging in active use, which supports the notion that digital platforms are a source of need satisfaction and not passive consumption.
Meanwhile, the results can also be attributed to the aspects of the Social Comparison Theory, which implies that people assess themselves in comparison to the lives of others (Festinger, 1954; Lin et al., 2016). The prevalence of such emotions as anxiety and sadness, and the presence of positive and neutral ones, shows that social media interactions may trigger both positive and negative emotions. The inability to overcome upward social comparisons may be enhanced by platforms such as Instagram, which focus on the display of content created by others, resulting in feelings of inadequacy or dissatisfaction (Błachnio et al., 2016; Reinecke & Trepte, 2014). The fact that the dataset has both positive and negative emotions implies that social media is a two-sided phenomenon that can be seen as a source of connectedness and a psychological distressor.
The differences in platforms that were identified in the study further highlight the need to contextualize digital behavior. Instagram users were found to be more engaged and intensive in their use, whilst other platforms like LinkedIn were found to have lower levels of use. This difference can be explained in terms of Media Richness Theory, which posits that the effectiveness of communication relies on the richness of media (Daft & Lengel, 1986). Rich, interactive, and multimedia communication platforms can potentially enable more emotional involvement and thus affect behavioral intensity and emotional consequences. On the contrary, less emotional engagement may be evoked by more functionally oriented platforms.
The other significant theoretical implication is the application of Self-Determination Theory, which highlights the importance of autonomy, competence, and relatedness in the determination of well-being (Deci & Ryan, 2000). Social media sites allow users to communicate (autonomy), receive attention in the form of likes and comments (competence), and socialize with others (relatedness). The fact that positive emotions like happiness and neutrality can be present in the results indicates that these psychological needs can be partially satisfied with the help of digital interactions. The co-occurrence of negative emotions, however, suggests that these needs are not necessarily met, especially in instances where engagement is not accompanied by the desired social feedback.
The predictive modeling outcomes also add to the conceptualization of digital behavior by proving that digital behavior measures can

be used to moderate emotional states. Though the classification model was found to be moderately accurate, misclassification between similar emotional labels like anxiety and sadness brings out the heterogeneity of emotional experiences. This observation is in line with the Affective Events Theory, which posits that emotional reactions are not caused by solitary actions but a set of events and interactions (Weiss & Cropanzano, 1996). When speaking about social media, the feelings of users are probably influenced by a complex of factors, such as the character of interactions, the content they listen to, and their psychological orientations.

In a more general sense, the results also correspond to the notion of Digital Social Capital that denotes the assets that a person acquires via online networks (Ellison et al., 2014). Intensive use, including frequent messages and comments, can lead to improvements in social capital by reinforcing social relations and creating a sense of belonging. Nevertheless, the skewed pattern of emotional outcomes implies that not every type of engagement can be beneficial to well-being. The advantages of social capital might be restricted by passive consumption or the absence of mutual exchange, which results in less positive emotional experiences.

Regardless of the contributions that the study makes, there are a number of limitations that cannot be ignored. To begin with, secondary data limits the manipulation of data collection protocols and the choice of variables. The sample lacks contextual factors like socioeconomic status, cultural context, or geographical location, which can affect both social media use and emotional well-being. Second, the categorical characteristics of emotional well-being as an operationalization restrict the level of psychological analysis, in that it fails to describe the degree or persistence of emotional states. Third, the study design is cross-sectional, which does not allow introducing cause and effect relationships, and it is hard to define whether the use of social media affects emotional well-being or the opposite. Lastly, the use of behavioral measures might not capture subjective experiences that cannot be observed in the data.

The future research can be based on the current study by addressing the limitations it has and increasing the area of analysis. It would also be helpful to conduct longitudinal studies that would analyze the changes in the use of social media and emotional well-being during a specific time frame, which would help to identify the cause-and-effect relationships. Secondly, it might be recommended to use the qualitative approach or mixed-method techniques to provide a more in-depth insight into the subjective experiences and motivations of users. The incorporation of cultural and contextual variables to unravel the differences in social media use and the resulting emotional outcomes in various social settings should also be taken into consideration in the future. Moreover, the implementation of more sophisticated machine learning methods can result in a more accurate prediction of models and a more in-depth understanding of the complicated interrelation between behavioral variables and emotional states.

Finally, the study concludes with the complexity of the connection between the patterns of social media use and emotional well-being, as digital behavior is predetermined by both the contexts of platforms and individual engagement patterns. The results underline the necessity to have a moderate perception of social media as a source of socializing and the source of emotional difficulties. The work provides a contribution to the overall discussion on the topic of digital human behavior by combining theoretical insights and empirical evidence, and providing a useful contribution to potential researchers, practitioners, and policymakers who want to ensure that the digital space is healthier.

5. Conclusion

The current research paper offers an in-depth examination of the use trends of social media and how they relate to emotional well-being in a cross-platform context. The results indicate that social media use is a complex phenomenon, with different degrees of interaction, preference for platforms, and emotional consequences. The findings indicate that, despite the fact that social media networks make communication, self-expression, and social connection easy, they also create an intricate emotional environment where good and bad experiences co-exist. The close relationship between intensity of use and measurement of engagement can be highlighted based on the fact that users are active participants in the development of their digital experiences. Meanwhile, the variety of emotional consequences points to the fact that more engagement is not necessarily associated with greater well-being. Platform-specific differences also support the idea that digital environments have a different impact on behavior and emotions, which is why it is crucial to conduct a contextual analysis. On the whole, the research adds to the existing body of knowledge about digital human behavior, showing that the use of social media is intimately connected to emotional experiences but not capable of explaining their intricacy. These results highlight the importance of a moderated attitude towards social media usage and demand additional studies that consider behavioural, psychological, and situational conditions to comprehend the connection between emotional well-being in online settings.

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