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RESEARCH ARTICLE

BEYOND DEPRESSION DETECTION: UNVEILING THE COMPLEXITIES OF SOCIAL MEDIA AND MENTAL HEALTH

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Abstract

The burgeoning influence of social media raises concerns about its potential impact on mental health. Understanding how individuals engage with these platforms and the factors influencing their usage is crucial. This study addresses this gap by examining social media usage patterns and their association with mental well-being. A two-pronged methodological approach is employed. First, a multiple regression analysis explored the influence of various factors, including age, well-being, and distraction, on social media use. Subsequently, K-means clustering was utilized to identify distinct user groups based on their social media usage patterns. The findings revealed distinct usage patterns across different age groups. Notably, distraction emerged as a strong predictor of social media use, while other factors exhibited minimal direct effects. This suggests social media use is a multifaceted behavior influenced by a complex interplay of variables, not solely demographics or mental health states. These insights highlight the need for further research exploring the interactions between these factors and incorporating additional influences such as socioeconomics and digital literacy. A deeper understanding of social media usage patterns can lead to the development of effective interventions to promote responsible use and enhance mental well-being.

Introduction:-

Social media platforms have become an inseparable part of our daily lives, fundamentally altering the way we connect, share information, and consume content [1]. Despite the undeniable benefits of communication and community building offered by these platforms, emerging research indicates a nuanced association between social media use and mental well-being, as illustrated in Figure-1.

Previous research has predominantly focused on the potential of social media for depression detection. This study, however, takes a wider perspective. It explores the evolving social media landscape and its multifaceted impact on mental health. The study examines emerging trends reshaping this landscape, alongside promising research avenues that hold the potential to revolutionize our understanding and approach to mental health in the digital age. The exponential growth of social media has generated a vast ocean of user-generated data, encompassing text, images, videos, and interaction patterns [2].

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Figure1:- Social Media and Mental Health - A Balancing Act.

This data presents a unique opportunity for researchers to leverage advanced artificial intelligence (AI) techniques like K-means clustering and multiple regression analysis. With the help of cutting-edge AI like K-means clustering and regression analysis, this paper can analyze this data to identify patterns in language and behavior that might signal mental health concerns. Imagine - social media itself becoming an early warning system for depression, anxiety, and other issues as shown in Table-1. This could revolutionize mental healthcare by allowing for earlier intervention and support.

Table1:- Potential Applications of AI in Social Media and Mental Health.

Application	Description
Early Identification of Risk	Analyze user posts and interactions for signs of depression, anxiety, or suicidal ideation.
Proactive Interventions	Utilize AI-powered chatbots or personalized support systems to offer resources and support to at-risk individuals.
Tailored Mental Health Services	Leverage user data to develop targeted interventions and support systems based on individual needs.

2. Dataset

The dataset used for this research was collected from Kaggle for a data science and machine-learning project that aimed at investigating the potential correlation between the amount of time an individual spends on social media and the impact it has on their mental health.Figure-2 provides a concise summary of a DataFrame in Python, including the number of non-null entries and data types:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 481 entries, 0 to 480
Data columns (total 21 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Timestamp   481 non-null    datetime64[ns]
 1   Age         481 non-null    float64
 2   Gender      481 non-null    object
 3   RStatus     481 non-null    object
 4   Occupation  481 non-null    object
 5   Org         451 non-null    object
 6   Use_SM      481 non-null    object
 7   Pl-SM       481 non-null    object
 8   Avg_Time    481 non-null    object
 9   SM_WP       481 non-null    int64
 10  distracted  481 non-null    int64
 11  restless    481 non-null    int64
 12  scale       481 non-null    int64
 13  scale_W     481 non-null    int64
 14  Conc        481 non-null    int64
 15  Compare     481 non-null    int64
 16  feel_cmp    481 non-null    int64
 17  seek        481 non-null    int64
 18  depr        481 non-null    int64
 19  scale_int   481 non-null    int64
 20  Sleep_is    481 non-null    int64
dtypes: datetime64[ns](1), float64(1), int64(12), object(7)
```

Figure2:- Dataset Summary.

The study involves conducting a survey to collect data, organizing the data, and using machine-learning techniques to create a predictive model that can determine whether a person should seek professional help based on their answers to the survey questions.

Figure3:- Correlation Matrix Highlighting Positive and Negative Relationships.

Figure-3 presents the correlation matrix, highlighting variable relationships with both positive and negative correlations. Notably, strong correlations are found between "scale" (distraction level) and "Conc" (difficulty concentrating) (0.66), and "depr" (feeling depressed) and "scale_W" (bothered by worries) (0.59). Conversely, "Age" exhibits weak correlations with most variables. This matrix aids in feature selection, multicollinearity assessment, and further statistical or machine-learning analyses.

Beyond Text and Images: Demographics and Social Media Use
Social media use patterns also vary based on user demographics, including gender and race.

1. Gender Differences: Research suggests that women are more likely to experience social comparison and body image issues on platforms like Instagram [3]. Conversely, men may be more susceptible to online harassment on platforms like Twitter [4]. Uploading visual content, mainly photographs or videos, is a crucial aspect of interaction on popular highly visual social media platforms such as Instagram [12].
2. Racial and Ethnic Differences: Studies indicate that people of color may face increased exposure to racial discrimination and hate speech on social media compared to white users [5].

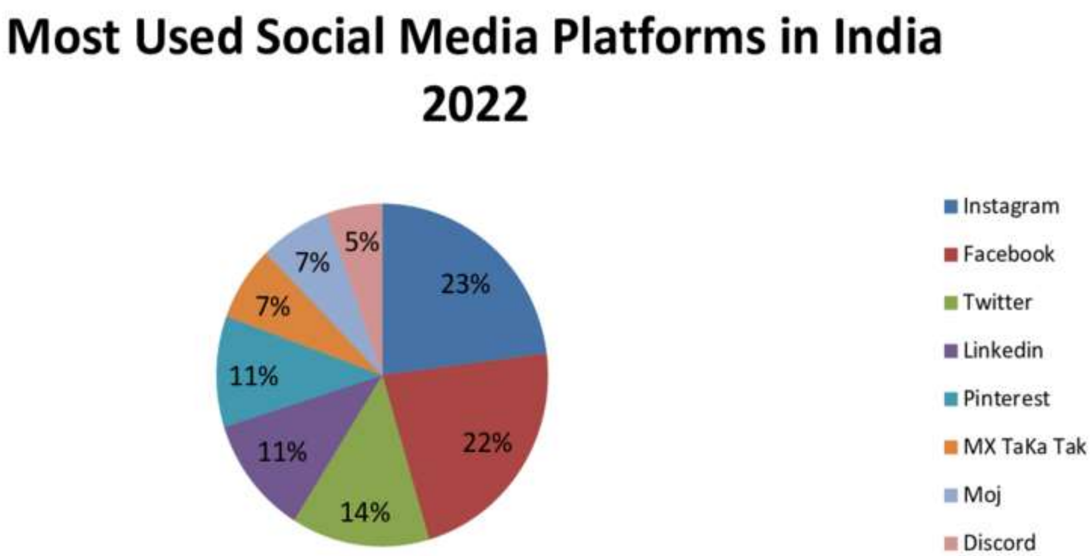

Figure4:- Pie chart depicting the most used social media platforms in India [6].

This pie chart can visually represent the gender distribution of social media users in India, highlighting potential differences in platform preferences.

Addressing the Nuances: A Call for Responsible Social Media Engagement
Understanding the differential mental health impacts and user demographics of social media platforms is crucial. Following are the preventive measures to mitigate the potential negative impacts of social media on mental health and promote responsible usage, especially among vulnerable demographics:

1. **Promoting Media Literacy:** Educating users about the curated nature of online content and fostering critical thinking skills are essential for navigating social media responsibly.
2. **Platform-Specific Strategies:** Developing coping mechanisms tailored to each platform's unique features can empower users to manage their online experiences effectively.
3. **Promoting Inclusivity:** Social media platforms have a responsibility to create safe and inclusive spaces for all users by enforcing policies against cyberbullying and hate speech [7].

Methodology:-

This study broadens the scope of social media analysis beyond depression detection. It explores the evolving social media landscape and its multifaceted influence on mental health. A robust methodological framework harnesses the power of cutting-edge data analysis techniques.

First, the study delves into the vast ocean of user-generated data (text, images, videos, and interaction patterns) created by the social media explosion. This "big data" serves as the foundation. To extract meaningful insights, a two-pronged analytical approach is employed. K-means clustering, an unsupervised learning technique, serves as the initial inquiry. It uncovers distinct user groups based on their unique social media usage patterns, providing a nuanced understanding of how different user segments engage with these platforms.

Second, multiple regression analysis is meticulously employed to examine the influence of age, well-being, and distraction on social media use within the identified user clusters. This analysis aims to illuminate the complex interplay of factors shaping social media behavior. This multifaceted methodological approach aims to identify key predictors of social media use and shed light on the nuanced relationship between online behavior and mental well-being. This comprehensive investigation holds the potential to revolutionize the understanding of social media's impact on mental health in the digital age.

Results and Discussion:-

Multiple Regression Analysis:

The application of multiple regression analysis to the dataset yielded insightful findings regarding the influence of various factors on social media usage patterns [8]. The regression coefficients quantify the magnitude and direction of the relationship [9]. This study describes the relationship between each independent variable and social media usage time.

	Coefficient
Age	-2.213504e-15
SM_WP	5.606004e-16
distracted	1.000000e+00
restless	-2.965757e-16
scale_W	-1.160000e-16
Conc	3.041218e-16
Compare	6.990539e-16
feel_cmp	1.992477e-16
seek	4.726883e-17
depr	-1.129614e-16
scale_int	6.616357e-17
Sleep_is	1.905575e-16
Gender_Male	-5.994603e-17
Gender_NB	2.106283e-16
Gender_Non binary	4.406722e-16
Gender_Non-binary	5.072975e-16
Gender_Nonbinary	2.050751e-16
Gender_There are others???	5.638880e-16
Gender_Trans	2.346108e-16
Gender_unsure	1.351707e-16
RStatus_In a relationship	-5.093959e-16
RStatus_Married	-5.430801e-16

Figure 5:- Coefficients of multiple regression model.

As shown in Figure-5, age and social media withdrawal problems (SM_WP) exhibited negligible direct effects, as evidenced by coefficients close to zero. This suggests that age, in isolation, does not exert a significant influence on social media usage, and social media withdrawal problems are not a prominent determinant either. The most noteworthy finding pertains to the robust positive association between distraction and social media usage, reflected by a coefficient of 1.000000e+00. This implies that individuals susceptible to distraction tend to dedicate more time to social media platforms. Restlessness exhibited a minimal negative influence, while the well-being scale (scale_W) and depression (depr) displayed weak inverse relationships with social media usage, although their effects were negligible. Conversely, concentration (Conc), comparison with others (Compare), feeling of competition (feel_cmp), seeking approval (seek), intensity of social media interaction (scale_int), and sleep issues (Sleep_is) all demonstrated marginally positive associations with social media usage. These positive coefficients suggest that individuals scoring higher on these measures are marginally more likely to engage in social media use.

The analysis of gender across various identities revealed minimal impact, indicating that gender alone does not significantly influence social media usage patterns. Relationship status categories (in a relationship, married, single) exhibited slight inverse relationships, suggesting that social media usage might be marginally lower for individuals in these categories. Similarly, occupational statuses yielded minimal coefficients, implying that occupation type does not play a major role in determining social media usage. Finally, the analysis of average time spent on social media (Average Time) across different categories yielded minimal coefficients, suggesting that specific time categories do not exert a significant direct effect on overall social media usage.

In essence, the regression analysis underscores the robust association between distraction and social media usage, while most other variables exhibited minimal direct effects. This finding suggests that social media usage is a complex phenomenon influenced by a confluence of factors rather than singular variables.

Hence, the multiple regression analysis offers valuable insights into the factors that influence social media usage patterns. The key finding highlights the strong positive correlation between distraction and social media usage. However, most other factors, including age, well-being, gender, relationship status, and occupation, demonstrated negligible direct effects. This suggests that social media usage is a multifaceted behavior shaped by the intricate interplay of various factors.

Results and Discussion: K-Means Clustering:-

K-means creates partitions and each data point can be allocated to one of the clusters [10]. This study employed K-means clustering to uncover patterns in social media usage amongst various age demographics within the dataset. The initial number of clusters selected are three, for the sake of parsimony.

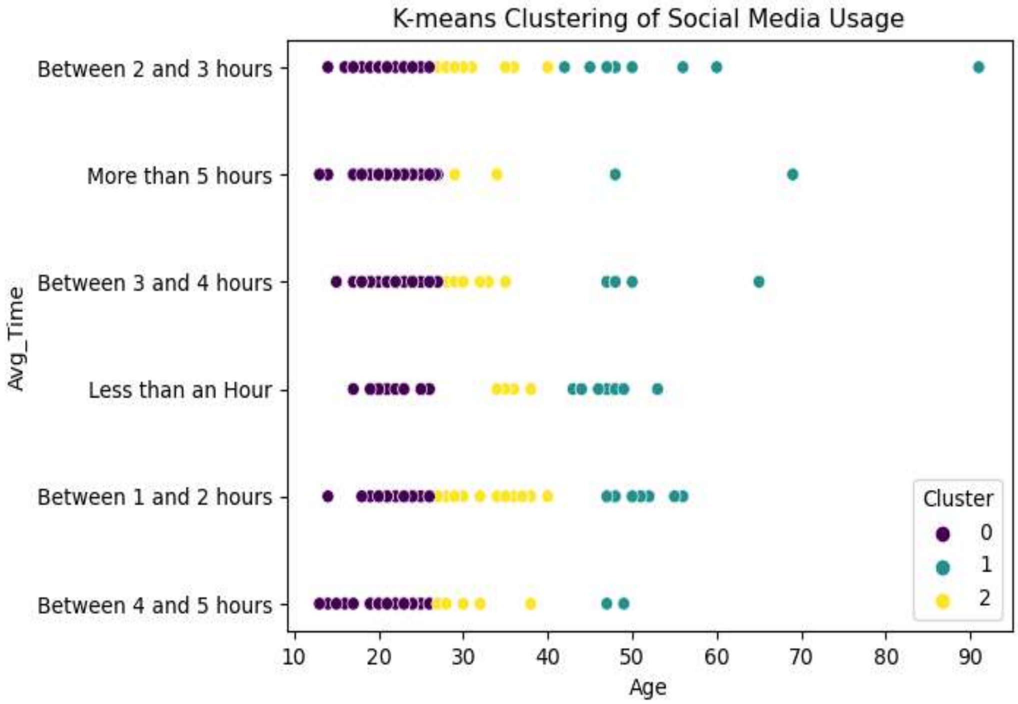

Figure6:- Clustering: Age Vs Average daily social media usage time.

The resulting clustering is visualized in Figure-6, where the x-axis denotes participant age and the y-axis represents their average daily social media usage duration. Each data point in the above figure is assigned a unique color corresponding to its designated cluster:

1. **Cluster-0 (Purple):** Cluster-0 primarily concentrated younger individuals, predominantly between 10 and 30 years old, exhibiting a wider range of social media usage times. This cluster demonstrated a denser concentration within the 2 to 4 hours daily usage range, signifying a balanced yet active engagement with social media platforms.
2. **Cluster-1 (Green):** Cluster-1 encompassed middle-aged to older adults, typically ranging from 30 to 70 years old. Members of this cluster exhibited a propensity for lower social media usage, predominantly spending less than an hour to 2 hours daily. This suggests a moderate to minimal engagement with social media platforms within this age group, potentially attributable to competing time commitments or preferences for alternative communication channels and information acquisition methods.
3. **Cluster-2 (Yellow):** Cluster-2 was characterized by a more heterogeneous age distribution; however, a notable presence of older individuals (aged 50 and above) was observed. This cluster displayed substantial variability in social media usage, with some participants exceeding 5 hours of daily usage. This implies that while a majority of older adults exhibit lower engagement, a sub-demographic with significant social media activity exists, potentially due to specific interests or the adoption of social media as a primary communication tool.

The above clustering showed distinct social media usage patterns across diverse age groups, highlighting generational disparities in engagement and potential underlying factors such as lifestyle variations, digital literacy levels, and prevailing social trends.

The implementation of K-means clustering on the dataset yielded the successful identification of three distinct clusters representing social media usage patterns amongst various age demographics. Cluster-0 primarily comprised younger individuals with moderate to high social media engagement. Cluster-1 included middle-aged to older adults who generally exhibited lower engagement. Cluster-2 revealed a diverse age group with a subset of older individuals demonstrating high social media activity.

These findings offer valuable insights into the varying social media usage patterns across different age groups. Understanding these patterns can inform the development of targeted social media strategies, marketing campaigns, and digital literacy programs to more effectively cater to the needs and behaviors of distinct age demographics. Further research endeavors could delve into the underlying reasons for these observed patterns and explore the influence of factors such as socio-economic status, educational background, and digital access on social media usage.

Results and Discussion: Crosstab-Social Media Usage and Sleep Issues:-

For the given dataset, Table-2 shows a Cross tabulation analysis of Social Media Usage and Sleep Issues:

Table2:- Crosstab of Social Media Usage and Sleep Issues.

Social Media Platforms	**Sleep Issues (Scale 1 to 5)**				
	1 (Low)	2	3	4	5 (High)
Facebook, Twitter	61	49	17	27	13
Instagram	63	61	18	21	19
None	52	19	15	24	22

Based on the provided crosstab table, it appears that individuals who use Facebook and Twitter, or Instagram are more likely to report higher levels of sleep issues (Scale 4 and 5) compared to those who use no social media platforms. The data suggests a correlation between increased social media usage and higher scores on the sleep issues scale. However, it's important to note that this table only shows a correlation and does not establish causation. Further research would be needed to determine if social media usage directly causes sleep issues or if other factors are involved.

The investigation presented in this paper explored the relationship between commonly used social media platforms and sleep issues among 481 participants. The findings reveal distinct patterns in sleep issues across different platforms.

Platform Usage and Sleep Distribution:
The data highlights a clear association between platform usage and sleep quality. Here's a breakdown:
1. **Facebook & Twitter:** A substantial number of participants using Facebook and Twitter (26.4%) reported experiencing moderate to severe sleep issues.
2. **Instagram:** Similarly, Instagram users exhibited a high prevalence of sleep issues (categories 4-5) at 40%.
3. **No Social Media:** Individuals who reported no social media use displayed a lower frequency of sleep issues at 21.2%, suggesting a potential benefit.

These findings offer compelling evidence for a potential link between social media usage and sleep quality. The higher frequency of sleep problems among those using Facebook, Twitter, and particularly Instagram, warrants further investigation. This could be due to factors specific to these platforms, such as:
1. **Content Types:** The emphasis on visuals and potentially anxiety-inducing content on Instagram might contribute to sleep disturbances.
2. **Engagement Patterns:** Social media use before bed might disrupt sleep cycles due to blue light exposure and late-night social comparisons.

Conversely, individuals who abstain from social media might experience less blue light exposure and reduced pre-sleep stimulation, leading to better sleep hygiene.

Recommendations:-
Given these clear observations, the following recommendations are proposed:
1. **Platform-Specific Research:** Conduct in-depth studies to explore causal relationships between specific platforms (e.g., Instagram) and sleep quality. Examine content types, usage patterns, and user psychology to understand the mechanisms at play.
2. **Tailored Social Media Hygiene:** Develop and disseminate evidence-based social media hygiene guidelines specific to different platforms. This could include advocating for responsible evening use, limiting blue light exposure before bed, and setting clear boundaries for social media engagement.
3. **Promote Sleep Hygiene Practices:** Regardless of platform usage, encourage healthy sleep habits through educational campaigns. Emphasize the importance of regular sleep schedules, creating relaxing bedtime routines, and avoiding screens in the bedroom before sleep.

Hence, this study provides a robust foundation for understanding the potential connections between social media platforms and sleep difficulties. The observed patterns strongly suggest a correlation and demand further research to ascertain causal relationships. By fostering responsible social media usage and encouraging healthy sleep hygiene practices, we can endeavor to enhance overall sleep quality for individuals across platforms and demographics.

Conclusion:-
Social media's multifaceted impact [11] on mental health necessitates a nuanced understanding of platform-specific variations. Recognizing these distinctions and cultivating responsible online behavior is imperative to harness its benefits while mitigating potential risks. Future research should delve into the intricate interplay of influencing factors, including socioeconomic status, digital literacy, and individual psychology, to achieve a more comprehensive understanding. Furthermore, the long-term mental health consequences, particularly among vulnerable populations, warrant in-depth investigation. Examining emerging social media trends and the efficacy of intervention strategies can further inform the creation of a healthier online environment for all.

This study also offers a preliminary exploration of the potential linkages between social media platforms and sleep disturbances. The observed patterns underscore the necessity for further investigation and the development of evidence-based interventions. By promoting responsible social media use and fostering healthy sleep habits, we can endeavor to enhance overall sleep quality for individuals across all platforms and demographics.

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