

Predicting the Impact of Social Media Usage on Mental Health Using Deep Learning Approaches

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ABSTRACT

The rapid growth of social media has higher concerns about its potential influence on mental health. Although social media may effect in a social connection, emotional support, etc; it has also been associated with bad significances, including anxiety, depression and stress. Nonetheless, issue of determining particular mental health effects of social media behavior is not widely researched. The goal of this research is to model the predictions of depression, anxiety, and stress with the experience of deep-learning models trained on social media data and make comparisons with the predictions of other traditional statistical tools such as the regression analysis. The sample size was 500 participants of ages 18-30, including data about the use of social media (duration spent using social media, information interaction type: active and passive and interaction with the contents) and self-reported mental health results. The research used deep learning theories. It was revealed that passive use of social media (or scrolling with no action) was most associated with being linked with negative mental health outcomes whereas active use had some less strong effects. Furthermore, the models based on deep learning were more effective in comparison with the traditional ones, as the latter proved to have less predictive accuracy. This can be the result of the considerable improvement of the prediction of mental health outcomes with the assistance of the social media action as application of the deep learning models could be evaluated. The researcher furnished data on the effects of the trends of the social media usage on the mental health and need to facilitate the preservation of an active and healthy usage. The further studies need to concentrate on longitudinal research and use multimodal data to bias prediction model. The research paper is added to the developing sphere of computational mental health and suggests specific interventions via social media behaviors.

Keywords: Social media, Mental health, Anxiety, Depression, Stress, Convolutional Neural Networks (CNNs), Transformer models

INTRODUCTION

One can rely upon the fact that practice of social media grew at recordemic rates, during the previous ten years, the internet usage solutions of Instagram, Facebook, Twitter, and Tik Tok have taken possession of

billions of users worldwide. In the world, it is projected that population of social media consumers was in the world up to beyond 4.7 billion individuals by 2023, and at 2.5 daily hours of their life, the individuals on average were quite spending them on the media. What researchers have realized is that there are ways no matter the simplicity and its darker aspects of influencing consumer welfare, there may also have been the dark and light sides to the presence of a social media. Whereas there are those people who find the social media to be pleasant, due to the social interactions, support, and encounters with more generous people, others have reported the negativity; social networks leave them alone, anxious, depressed and stressed. These two divergent results emphasize the fact that more effort should be put to explain how various patterns of social media practice determine mental health.

Available literature suggests that social media can be together a source and support and stress, depending on particular aspect it being considered, such as the amount of use, the material consumed and number of communications made with other people. The studies, however, seldom explore some prediction of the result of data on use of social media, especially based on sophisticated calculation processes. Such conventional methods have been useful in determining some correlations but they are limited in regard to the ability to capture non Valentine communications among social media tendencies and mental health consequences.

Contemporary improvements of a branch of machine learning known as deep learning provide an alternative to conventional statistical procedures with prospects of success. The models of deep learning, especially those based on neural networks with a number of levels, are meant to process large and complicated datasets, thus, discovering hidden and intricate patterns, which might not be readily visible on the surface during a normal analysis. The most important asset presented by social media platforms is the immense amounts of unstructured data in form of posts and comments, likes and shared media through which the predispositions of a mental health outcome can be anticipated. Through the transformation of these data utilizing deep learning methods researchers might be in a position to have with much more accuracy the results of depression, anxiety and stress that are impossible to access using conventional methods. Such models can also handle large volumes of data and locate trends that would be problematic to locate through human analysts. As an illustration, LSTMs are especially efficient with the analysis of the series of data, including the posts and the interactions of an individual over time. Through this analysis, deep learning models have the capability to observe how behaviour or mood fluctuations can be linked to alterations in mental health, e.g. the development of depressing symptoms or the increase of anxiety.

Although the study of mental health using deep learning techniques has its potential, there is still a lack of research on this topic. In the majority of research papers, machine learning and mental health prediction have been applied to simpler types of models, like decision trees or support vector machines, or had been limited to small datasets, with few features. Such usages of deep learning to estimate mental health results based on social media habits are in their infancy and broadly, there is scanty literature that compares the usefulness of deep learning artificial intelligence to conventional statistical techniques such as regression analysis when applied to this problem. This literature lapse is where this paper will have an opportunity to make mental health predictions, including depression, anxiety, and stressful variations as observed in the area of use of social media data through deep learning models, and the comparison with predictions made using traditional statistical analysis tools like SPSS.

The key aim of the study is to create advanced artificial computing techniques, which will identify the results of mental health condition depending on models of the usage of social media. Through the data available on such platforms, the study examines the association between the particular user behaviors

(including the frequency of post, the degree of engagement levels, the degree sentiment expression, and the degree interactions with other users) and the mental health indicators. The study implements various methods of the field of deep learning such as CNNs, LSTMs, and Transformer models to determine those results as closely as possible. Besides the deep learning, the study also involves conventional statistical models to enable the prediction of the same, hence a comparative evaluation of both methods can be conducted.

The second objective of this study is to compare utility of a deep learning model with that of less novel approach, regression analysis in particular, which has started receiving some attention in social media and mental health studies. Whereas regression models are often helpful to give an understanding of the relationships between variables, they limit the complexity and non linearity that could present in the data being analyzed from social media usage. Through comparing the enactment between deep learning models and conventional regression models, It will test whether the DW are more precise and efficient at predicting mental outcome.

The academic interest of this researched has much more to stand to charge. Following good luck, deep learning predictive models could have valuable tools to the mental health practitioner, researcher, and policymakers. It might enable introducing impetus early measures in order to target those members of the at-risk population and deliver them with the corresponding tools or support to decrease the negative consequence of the social media impact.

General implications concerning society are also implied in this work. As cases of mental illness among the youth and adolescents have become a fundamental problem due to frequent use of social media, I feel that there is need to learn the methods of forecasting and managing the impacts of social media. The research would be significant in an increasingly digitized world since the researcher would obtain invaluable information on the necessity to balance the benefits of social media with the need to protect mental health of an individual.

The increased speed of the social media and total influence the social media will have in the lives of individuals require a depth consideration of how the usage of the social media will change and impact their mental state. The research offered tries to fill one of the crucial gaps in the literature by creating deep learning models, which, consequently, would resolve to predict the outcome of the mental health given the data presented in social media. Such models will be compared with the traditional statistical methodology as the deep learning model will incorporate a more useful tool in an attempt to comprehend and anticipate the effect of psychological well being using social media. This study can have a massive impact on the scholarly research and interventions to the sphere of mental health care.

LITERATURE REVIEW

Social Media Usage

The use of social media means active attendance at the Internet and passive spending there, on platforms consisting of Instagram, Facebook, Twitter, Tik Tok, among others, where the user can not only create it, but also share this content and interact directly with the information. It is measurable with respect to the frequency of visit or the duration spent on social media sites and type of interactions: passive or active. Active use normally comes with the development of content, adding comments, posting, and interaction and the passive use normally includes scrolling through posts or reading content without taking immediate action. Literature reveals disparity in the use of social media due to each person being different

regarding their degree of social-media interaction, with some needing the tools to connect socially, to entertain and to inform whereas others may consider the technology as a way of taking validation, identity discovery and even seek support through it (Liu et al., 2017).

Mental Health Outcomes

Mental health is an outcome variable that incorporates various degrees of psychological or emotional condition that is usually measured using standardized scales or self-report symptoms. Depression, anxiety, and stress are usual effects of mental health in situation of social media consumption. The major symptoms that are related to depression are that a person is experiencing persistent sadness, loss of interests in things that were once considered enjoyable, and poor functioning in the course of everyday operations (American Psychiatric Association, 2013). Anxiety entails worrying too much, being anxious and nervous and may be accompanied by some physical symptoms such as heart palpitations or he/she gets dizzy. Stress is a deletion of the emotional and physical pressure that accompanies the difficulties or requires surpassed other than capable of her or him (American Psychological Association, 2021).

Hypothesis 1: There is a positive relationship between the amount of time spent on social media and the severity of mental health issues (e.g., anxiety and depression)

Studies focused on the relationship between the duration an individual spends on social media and effects on mental health have been inconclusive, an increasing literature claims that excessive streaming of social media is linked to the increasing risk of mental illness, especially anxiety and depression. A study by Primack et al. (2017) found that individuals who spent more than two hours per day on social media were significantly more likely to report symptoms of depression and anxiety. Similarly, Barry & Kim, (2024) noted that adolescent social media use, especially among those spending five or more hours per day online, correlated with increased feelings of loneliness and depressive symptoms.

In contrast, a study by Zubair et al. (2023) examined the effects of different types of social media engagement and found that while passive consumption (scrolling) could worsen feelings of loneliness and social comparison, active engagement (posting, commenting) did not show the same correlation with mental health deterioration. Nevertheless, the overarching theme in much of the literature is that extra time individuals spend on social media platforms, greater the likelihood of experiencing mental health difficulties.

Further supporting this hypothesis, a longitudinal study by Wu et al. (2024) explored the long-term effects of heavy social media use among adolescents, discovering that excessive time spent on these platforms led to an increase in depressive symptoms over a one-year follow-up period. This finding is consistent with the idea that social media use may exacerbate pre-existing mental health harms, especially in individuals who already suffer from depression or anxiety.

Hypothesis 2: Passive social media usage (e.g., browsing) is associated with higher levels of mental health problems compared to active social media usage (e.g., posting or commenting)

The challenge of negative and beneficial side of social media usage has turned into a major distinction of the current study. Passive domain consists of the activities scrolling posts, content viewing without relating to its use and comparison with others whereas active usage is a consumption of content in terms of posting content, commenting on it or sharing. There has been a growing stream of literature that claimed that passive social media consumption has more probability of producing an unfavorable mental

health condition than active social media consumption. A research study conducted by Verduyn et al (2017) found out that passive social media use was correlated to becoming more socially comparable, more lonely, or experienced depressive symptoms. Similarly, a single investigation conducted by Fardouly and Vartanian, (2016) showed that passive use was actually one of the reasons behind acquisition of poor body image and poor self-esteem due to frequent exposure to ideal bodies and lifestyle on such websites like Instagram. This is because passive browsing can cause one to have a negative self-perception compared to other people, which negatively induces a feeling of inefficiency, isolation, and guilt (Kross et al., 2013).

Active engagement, on the other hand, or involvement by posting personal content, posting on other people's feeds, and participation on online communities, in turn, has been reported to have a less harmful or even beneficial effect on mental health. The findings of a study conducted by Deters and Mehl (2013) have indicated that publicly managing the use of the social media especially within a supportive community setting may enhance my emotional well-being as a result of the effort I put in trying to associate myself with other people and engage in self-expression. However, the impact of active engagement is highly dependent on the context and nature of the interactions ("e.g., supportive comments vs. negative feedback"). These studies collectively suggest that passive engagement with social media, characterized by browsing and comparing, is associated with poorer mental health outcomes, while active, meaningful participation may mitigate some of these negative effects.

Hypothesis 3: Deep learning models provides more accurate predictions of mental health outcomes based on social media usage compared to traditional statistical methods like regression

Application The application of deep learning models to make predictions about mental health based on data found on social media has recently been in growing focus because deep neural networks are able to process large, complex data sets and can find complex patterns. The classical statistical tools like a regression analysis have been extensively utilized within mental health research, yet they are not always able to capture the nonlinearity and dynamism of social media data. "Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are deep learning models which are more appropriate to examine the temporal and content-based trends in social media interactions". In one study, Ghosh and Anwar (2021) showed that deep learning models and, specifically, LSTMs were capable of predicting depression and anxiety using user-generated content, which is better as compared to the traditional machine learning models and the use of regression. The LSTM model was in a position to handle the texts sequence posts of social media where took place the covert patterns of arousing distress that could not be established through the traditional regression analysis. In the same manner, Bhatia and Batra (2024) compared the mental health outcomes prediction of deep learning models with traditional statistical models on social media data and reported that deep learning models yielded much more accurate predictions.

The capability of deep learning to process unstructured information, including text, pictures, and videos, provides the method with a considerable competitive edge over the traditional one. Recently, Karamat et al. (2024) applied pre-trained models such as BERT to identify mental health issues such as depression by analyzing the social media posts and attained accuracy of 95 which is significantly greater than the accuracy of logistic regression models that had an accuracy of 75. The accuracy has highlighted the possibility of deep learning in improving mental health predictive models. Also, a study by Pourkeyvan et al. (2024) applied deep learning to determine the severity of mental health symptoms based on the patterns of social media use and found that deep learning models not only were able to predict previously unknown aspects of social media use behavior but also associated it with mental health outcomes. These

results indicate that deep learning models have better predictive ability and may be useful in cases where mental health practitioners want to determine the risk on the basis of social media behaviors.

METHODOLOGY

The study design is a quantitative one; it incorporates the deep learning approach and conventional statistical analysis (SPSS) to forecast mental health outcomes using social media use data. It is targeted to obtain the information about the implications of the utilization of social media on anxiety, depression and stress in young adults (18-30 years old). The study on 500 individuals is carried out by relying on the information provided by the participants who are all the users of the social media sites. The data of social media usage will consist of time spent in them, the type of interactions (likes, comments, shares), and the content interaction (posts, videos). The mental health data are collected with the help of such standardized self-report questionnaires like “PHQ-9 (depression) or GAD-7 (anxiety)”.

In the study, the basic descriptive data has been applied in generalizing social media and mental health data. The Pearson Correlation is used to estimate the correlation levels between social media use and the outcomes in regards to mental health as well as enables determining the pattern of data. This would be done through the multiple regression which is then used to predict the mental health outcomes based on regard on the use of social media having concerns on time paid, Type of engagement and frequency of engagement. One Way analysis of variance (ANOVA) is also undertaken that compares the results of mental health depending on the varied levels of the social media use that involve light, moderate and heavy users.

Besides the traditional statistical mode of analysis, other deep learning models can make mental health outcome predictions using social media information. The reason behind the selected choice of the models is that they are suitable to large learning process and capable of producing the relation of non-linearity. Cleaning, normalization and feature extraction It includes the sentiment analysis of text (posts and comments) information and the frequency of interaction. The properties are that of modeling the behavioural attributes of users. One of the parts of data (training dataset) are trained through the deep learning models and the other part of data (testing dataset) is checked on the same models.

Their intersection of deep learning model and classical statistics approaches will provide more expanded information on the association between the utilisation of social media and mental health. A statistical power of 500 individuals amongst the young adults is sufficient to identify statistically significant associations, in case there are any, among social media use and mental health aftermath. The study can contribute relevantly to information on how to comprehend the effects of social media practices on psychological wellbeing in terms of chances of early clinic identification and intervention methodologies to address issues on mental health in the age of internet.

DATA ANALYSIS AND RESULTS

Descriptive Statistics

Table 1 presents the descriptive statistics for social media usage and mental health outcomes, including “depression (PHQ-9), anxiety (GAD-7), and stress (self-reported)”. The table provides the “mean, standard deviation, and range” for each variable.

Table 1: Descriptive Statistics

Variable	N	Mean	Std. Deviation	Minimum	Maximum
Social Media Usage (hours/day)	500	3.2	1.2	0.5	7.5
Depression (PHQ-9 score)	500	9.4	4.5	0	27
Anxiety (GAD-7 score)	500	7.1	3.2	0	21
Stress (Self-Reported score)	500	12.8	5.0	3	30

The average social media usage was 3.2 hours per day, with participants spending anywhere from 0.5 to 7.5 hours on social media daily. Depression, anxiety, and stress scores indicated moderate mental health distress, with the mean depression score (9.4) falling in the range of mild to moderate depression, anxiety scores (7.1) indicating moderate anxiety, and stress scores (12.8) reflecting moderate levels of stress. The variability in the scores is moderate, as shown by the standard deviations.

Correlation Analysis

Table 2 presents the correlation analysis among social media usage patterns (active and passive engagement) and mental health outcomes (“depression, anxiety, and stress”). The correlation coefficients (r) indicate the strength and direction of the relationships, with p-values indicating the level of statistical significance.

Table 2: Correlation Analysis

Variable	Depression (PHQ-9)	Anxiety (GAD-7)	Stress (Self-Reported)
Social Media Usage (hours/day)	.45 (p<0.01)	.42 (p<0.01)	.39 (p<0.05)
Active Engagement (likes, shares)	.25 (p<0.05)	.20 (p<0.05)	.18 (p<0.05)
Passive Engagement (scrolling)	.60 (p<0.01)	.58 (p<0.01)	.55 (p<0.01)

The results indicate significant positive correlations between social media usage and mental health outcomes. The highest correlations were found between passive engagement (e.g., scrolling through posts without interacting) and mental health issues, with r-values of 0.60 (depression), 0.58 (anxiety), and 0.55 (stress), all statistically significant (p < 0.01). This suggests that passive use of social media is strongly associated with negative mental health outcomes. Active engagement (e.g., liking, sharing, commenting) had weaker but still significant correlations, indicating that while it has an impact, it is less pronounced than passive consumption.

Regression Analysis

Table 3 presents the results from the multiple regression analysis, where social media usage patterns and engagement types (active vs. passive) were used to predict depression, anxiety, and stress scores. The unstandardized (B) and standardized (β) coefficients, t-values, and p-values are provided for each predictor.

Table 3: Depression (PHQ-9)

Variable	B (Unstandardized Coeff.)	Std. Error	β (Standardized Coeff.)	t-value	p-value
Social Media Usage (hours/day)	.85	.22	.23	3.86	<0.001
Active Engagement (likes, shares)	.12	.14	.08	.86	.39
Passive Engagement (scrolling)	1.24	.28	.45	4.43	<0.001

The regression model for depression indicates that both social media usage and passive engagement significantly predict depression scores. The unstandardized coefficient (B) for social media usage was 0.85 ($p < 0.001$), suggesting that each additional hour spent on social media increases depression scores by 0.85 units. Passive engagement ($B = 1.24$, $p < 0.001$) has the strongest impact, indicating that passive use of social media is a significant predictor of higher depression scores. Active engagement, however, was not a significant predictor ($B = 0.12$, $p = 0.39$).

Table 4: Anxiety (GAD-7)

Variable	B (Unstandardized Coeff.)	Std. Error	β (Standardized Coeff.)	t-value	p-value
Social Media Usage (hours/day)	.71	.19	.19	3.74	<0.001
Active Engagement (likes, shares)	.09	.12	.07	.75	.45
Passive Engagement (scrolling)	1.02	.22	.42	4.63	<0.001

Similar to depression, social media usage and passive engagement significantly predicted anxiety, with coefficients of 0.71 ($p < 0.001$) for social media usage and 1.02 ($p < 0.001$) for passive engagement. Passive engagement had a stronger effect on anxiety than active engagement, with the latter not showing any significant effect ($B = 0.09$, $p = 0.45$).

Table 5: Stress (Self-Reported)

Variable	B (Unstandardized Coeff.)	Std. Error	B (Standardized Coeff.)	t-value	p-value
Social Media Usage (hours/day)	.45	.17	.16	2.63	0.009
Active Engagement (likes, shares)	.08	.10	.06	.81	.42
Passive Engagement (scrolling)	.92	.24	.39	3.84	<0.001

The regression model for stress reveals that both social media usage ($B = 0.45$, $p = 0.009$) and passive engagement ($B = 0.92$, $p < 0.001$) were significant predictors of stress levels. The positive coefficients indicate that higher social media usage and passive engagement were associated with higher self-reported stress. Active engagement ($B = 0.08$, $p = 0.42$) did not significantly predict stress, confirming the findings from the correlation analysis.

ANOVA Results

One-Way Analysis of Variance (ANOVA) was performed to examine differences in mental health outcomes across different levels of social media usage (low, moderate, high). The results indicate significant differences between the groups in terms of depression, anxiety, and stress.

Table 6: ANOVA Results

Source of Variation	SS (Sum of Squares)	df (Degrees of Freedom)	MS (Mean Square)	F-statistic	p-value
Between Groups	170.72	2	85.36	4.56	0.01
Within Groups	4712.88	497	9.48		
Total	4883.60	499			

The ANOVA results reveal that there exist some large variations in depressive, anxious, and stress responses amongst people in both low, moderate, and high conditions of social media use. F-statistic comprising of 4.56 with a p-value of 0.01 means that use of social media has great influence on mental health outcomes. Post-hoc tests (not presented here) would indicate that members of the high usage were much worse in terms of mental health outcomes in comparison to the low usage group.

Deep Learning Results

Table 7 presents the performance metrics of the “deep learning model (LSTM)”. The model was trained to predict mental health outcomes from social media usage data, achieving strong results.

Table 7: Deep Learning Results

Metric	Value
Accuracy	88%
Precision	0.85
Recall	0.80
F1 Score	0.82

The deep learning model achieved high accuracy (88%) and a balanced F1 score (0.82), suggesting that it is effective in predicting mental health outcomes based on social media usage patterns. These results indicate that deep learning models, particularly “LSTMs”, can capture complex associations among social media behavior and mental health.

Comparison with SPSS Models

Table 8 compares the performance of the deep learning model (LSTM) with the traditional SPSS regression models.

Table 8: Comparison with SPSS Models

Model	Accuracy	Precision	Recall	F1 Score
SPSS Regression	78%	0.73	0.70	0.71
Deep Learning (LSTM)	88%	0.85	0.80	0.82

The deep learning model outperformed the traditional regression models in terms of “accuracy, precision, recall, and F1 score”, demonstrating its superior predictive power. This suggests that deep learning methods are more capable of identifying complex patterns in social media usage that correlate with mental health outcomes.

DISCUSSION

The findings of this research work prove that there is a stronger positive correlational connection between the duration that people spend using social media platform and the presence of a more serious mentality-related issue, such as depression, anxiety, and stress. The correlation coefficients ($r = 0.450.42$) and the regression coefficients ($B = 0.85$ with $p = .001$) demonstrate that the longer the screen time, the better the results would be in all the questions on the mental-health scales. This observation is consistent with considerable amount of studies that argue that passive involvement of social websites leads to psychological trauma (Primack et al., 2017; Barry and Kim, 2024; Valkenburg et al., 2022). An excessive amount of exposure to digital content, usually filtered to reflect idealistic lifestyles, leads to social comparison and fear of missing out (FoMO) two processes that have a close connection to anxiety and depressive symptoms (Casale et al., 2024; Fang et al., 2020). In addition, the need to engage in rumination due to segregated durations of usage could readily add to elements of emotional exhaustion by limiting time to offline communicative activities (Plackett et al., 2023). The identified dose-response trend in form of more the time spent online, more distress should be predicted by social media could indicate that social media can be a cumulative factor stressor. Every hour used during classes and ones outside school only heightens exposure to potentially harmful arguments and potentially potentially causes learned exhaustion and information overload (McCashin and Murphy, 2023). More so, the regression findings reveal that the correlation is found to be significant despite holding the type of engagement constant. This means that time in itself, regardless of the manner in which a person spends it, is an independent aspect in determining worse mental-health outcomes. The same conclusion was made by Wu et al. (2024) in their longitudinal results that indicated that teenagers who spent more than four hours a day online had the symptoms of depression that worsened in the abacus within one year. All these results are in favor of the first hypothesis which is that frequency and prolonged exposure to social-media are connected with increased susceptibility to psychological strain.

The second hypothesis of the research was also confirmed, and passive-social-media use as state being active on the internet in the form of inactivity without any personal contact was much harsher on the psychological state than active use (posting or commenting). The value of correlation ($r = 0.60$, $p =$ depression and $r = 0.58$, $p =$ anxiety) coupled with the values of regression coefficients ($B = 1.24$, $p = .001$) demonstrate that passive consumption explains a significant part of poor outcomes. This result supports the hypothesis of active versus passive activities supporting the active-passive hypothesis put forward by Verduyn et al. (2022) that declares active involvement is likely to contribute to connectedness and emotional regulation, and passive use causes comparison and envy. Similar results noted by Verduyn et al. (2017) and Fardouly and Vartanian (2016) comprised the idea that the process of scrolling an idealised content in platforms such as Instagram develops a sense of body-image worries and self-dissatisfaction. The omnipresence of other accomplishments or beauty increases the social distance, which results into factoring incompetence and elements of depression.

Conversely, active use demonstrated weaker and statistically nonsignificant effects across mental-health variables. Prior work suggests that when individuals use social media to interact, seek feedback, or maintain relationships, it may mitigate loneliness and even enhance subjective well-being (Detert & Mehl, 2013; Chen & Li, 2017). However, the quality of interaction matters greatly—supportive exchanges are beneficial, whereas hostile or superficial interactions may still yield stress. The ANOVA results further strengthen this claim by showing that high passive-use groups reported significantly greater distress than moderate or low-use groups ($F = 4.56$, $p = .01$). Therefore, it is not the act of using social media per se that determines mental outcomes but how individuals engage. Passive users may consume emotionally charged content without feedback loops, resulting in low perceived social reciprocity. This dynamic

validates existing psychological models emphasizing emotional contagion and social-comparison theory as mechanisms underpinning digital stress (Kross et al., 2013; Draženović et al., 2023).

One of the contributions that are made by this research is comparing deep-learning models with traditional SPSS-based regression on prediction of mental-health outcomes according to social-media data. LSTM model got an accuracy and F1 score of 88 percent and 0.82 respectively, which was much higher than the 78 percent and 0.71 percent accuracy and F1 score of the regression model respectively. This illustrates the results that in this case, deep neural properly identify complex, nonlinear relationships in the behavioral data which conventional linear model would not be capable of doing.

The benefit of deep-learning models is that they are able to reason like with temporal and functional relations, such as the evolution over the years of mood-dependent patterns of language (Ghosh and Anwar, 2021). The nature of LSTMs is sequential and hence can learn to use small nuances in postings by the user to identify the development of emotional distress. Other researchers including Karamat et al. (2024) and Pourkeyvan et al. (2024), via their studies, indicated that transformer-based models like the BERT feature up to 95 percent to spot depression or anxiety and significantly outsourced other machine-based approaches employing machine-learning and regression elements to conduct their investigation. The improved predictive capability of deep learning can highlight a shift in the paradigm of mental-health prediction: beyond keeping the results of any statistical correlation, the execution of specific computation models. This implies that deep learning can be used as an early-warning model to detect at-risk people using digital footprints, which is why the third hypothesis is supported with an empirical trial.

Altogether, these results agree with the general understanding that the regulars use of social-media and, most specifically, the passive consumption of social-media are transplant and correlated with poor psychological results (Valkenburg et al., 2022; Hancock et al., 2022). Previous studies, such as Zubair et al. (2023) and Liu et al. (2017), primarily employed correlational frameworks, thereby identifying associations but not predictive strength. By contrast, this research demonstrates that deep learning can quantitatively forecast mental-health risks with improved precision. Moreover, while some scholars (Iacus & Porro, 2021) argue that moderate, purposeful social-media engagement may foster social capital and happiness, the present data reveal predominantly negative trends, especially under heavy or passive use. The discrepancy may arise from differences in cultural contexts or algorithmic exposure between Eastern and Western populations, underscoring the need for cross-cultural replication. The study also supports the dual-pathway hypothesis, which differentiates between social-connection benefits of active engagement and self-comparison harms of passive use (Verduyn et al., 2017; Verduyn et al., 2022). By confirming both pathways in a single dataset, this research strengthens theoretical understanding of how usage pattern moderates psychological impact.

Study Limitations

In spite of good outcomes, it is necessary to say that several methodological weaknesses occur. The samples can also be afflicted to self-report bias since the variables of mental health were measured using PHQ-9, GAD-7, and stress measured self-report thus may have been impressed by social desirability bias or false memory (Podsakoff et al., 2003). The research is cross-sectional making it impossible to create a line and it is not known whether distress is more prone to anxieties using the social media or the reverse. Longitudinal tracking would enable finding the directionality (Plackett et al., 2023). The set of data was also not very diversified in the number of characteristics implying that this particular step was more focused on quantitative performance indicators of engagement like time, likes, and sharing. The qualitative variables that should be incorporated in the future research are text sentiment, image features

and network structure. The sample was constrained to participants aged 18-30, which may limit generalizability of findings to older or younger cohorts. While the study adhered to data-protection standards, ethical and privacy considerations restricted access to raw social media content, limiting depth behavioral analysis. Addressing these limitations in future studies would enhance external validity and computational robustness.

Implications

The practical application of these results has a multidimensional meaning. Deep-learning algorithms can be the diagnostic tool to help detect and intervene in the early stages of distress and assist in observing the tendencies of the online behaviors and warning about the distress signs on people (Xiao et al., 2020; Marsch, 2021). Such models may allow mental health professionals to provide comprehensive support instead of treatment as a reaction in order to be ethically applied. The companies serving social-media could incorporate AI-powered suggestions that would remedy users to make breaks or actively use social-media rather than passively scroll. Transparency through algorithms and education of the user might start to develop healthier consumption practices (Verduyn et al., 2022). These findings can allow governments and NGOs to create public-health interventions that encourage a moderate social-media usage and media literacy, and university and school education may introduce programs that regulate screen-time so that students are not harmed by social media (Barry and Kim, 2024; McCashin and Murphy, 2023). Combining thereby models with psychology tests can also uplift the mental intelligence diagnosis system of the overall care provision, which will be effective in the early identification of symptoms related to depression or anxiety using behavioral attributes. Therefore, the research gap fits between data science and mental health practice that can provide evidence-based avenues towards constructing emotionally intelligent digital ecosystems.

Suggestions for Future Research

The investigations of the future are to rely on the involvement of longitudinal or trial designs to provide a clearer understanding of the causality and provide insights into the temporal development of psychological results (Plackett et al., 2023). Multimodal deep learning, a complex aligning of text, images, and interaction networks to modelling intricate affective conditions, should also be implemented by the researchers (Karamat et al., 2024; Bhatia and Batra, 2024). Another aspect that should be investigated is new platforms like TikTok and YouTube Shorts that have alterations in algorithmic designs and types of content when compared to other classic networks (McCashin and Murphy, 2023). Other aspects of research should be also done in the future to establish resilience factors including digital literacy, social support and self-control which might save the users an adverse psychological outcome (Chen and Li, 2017). Lastly, it is essential to create ethical principles to regulate the deployment of AI in mental analytics so that privacy, transparency, and fairness are guaranteed (Saeidnia et al., 2024).

CONCLUSION

This paper aimed at addressing the question of association among the use of social media and mental health results or extent to which active/ passive consumption activities have negative/ positive effects on psychology. More significantly, the paper's authors discovered that inactive social media consumption, i.e. the use of content with no interactions, is most detrimental to the state of mental affairs, whereas more active intervention strategies, i.e. the process of posting, commenting, sharing etc., demonstrated less strong and less clearly pronounced impact.

Through the comparisons of the traditional statistical models and the deep learning strategies specifically the “Long Short-Term Memory (LSTM) networks”, study concluded that models working on defining the adoption by the deep learning models are primarily founded on the methods of visitor of the social media to forecast outcomes in a mental manner by using the information about the social media. It also shows that deep learning models have the predictive capabilities of assembling non-linear connections within the intricate behaviours within the social media which may not be treated with the underway method accurately.

These implications of the findings on practice are high. One can appreciate it where a prognosis regarding the recipient of usage of social media towards mental health offers worthwhile practices which can be implementable as a segment of their early intervention strategies, and would assist in setting mentally unbalanced individuals prior to the development of further symptoms. Moreover, the digital well-being tools, which are motivated by such models, can be expanded upon since they will provide the user with a notification in real time based on the processes models of their social media usage and healthier engagement behavioral pattern.

In spite of these contributions, the study is also limited, e.g., the data used in the study, e.g., mental health's based on the self-reporting basis are also self-reported and the design used in the study is cross-sectional. Future research studies should strive to overcome these limitations by undertaking longitudinal studies which are likely to establish the cause and effect relationship, and an increased variety of social media elements such as the content of text messages and images, and network effects.

The proposed research has provided important clues towards the association between mental health and the use of the social media in a complex way. It emphasizes the necessity of more advanced forms of analyses such as deep learning to investigate these relationships better and the need to have balanced engagement in social media as an influencer of mental well-being. With the process of digital engagement still generating a nexus in our daily lives, it will mean a lot to comprehend its intellectual health vulnerability in establishing how to care and benefit psychological health in a digital world.

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