Mental Health Studies: A Review

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Abstract Mental health is a predominant issue in the United States. Conversations and research around mental health have increased in the past few years. This review examines and categorizes research that has been conducted regarding social media and its impact on mental health into three main categories: (1) Data Collection, Self-Reporting Surveys, and Reviews; (2) Data Collection with Machine Learning Applications; and (3) Modeling of Mental Health Using Survey Data and Machine Learning. Summary tables of risk factors studied, machine learning techniques, and social media sites studied or where data was gathered from are included.

Keywords Mental health · Social media · Machine learning · Modeling · Well-being

1 Introduction

Mental health is defined as emotional, psychological, and social well-being [1]. These are not independent of one another. Social well-being is associated with the development and maintenance of meaningful relationships with others, from which value and a sense of belonging within one's social group is derived [33]. Having a positive mental state enables one to have a stable emotional state, thoughts, and behaviors. It can also allow an individual to realize his or her own potential, work productively, cope with the normal stresses of life, and make positive contributions to society [5]. Being mentally healthy predominantly means having positive characteristics such as a feeling of purpose, contentment, maintaining fulfilling relationships, and participating in life to the fullest [5]. On the other hand, negative mental health may make it difficult to manage thoughts, feelings, or actions in response to daily stressors [7].

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H. Pham (ed.), *Applications in Reliability and Statistical Computing*, Springer Series in Reliability Engineering, https://doi.org/10.1007/978-3-031-21232-1_15

Focusing on mental health can improve physical health, increase productivity, and mitigate stress.

Mental health impacts every person even if they are unaware of it. According to Anwar [1], more than 40 million adults in the United States have an anxiety disorder, but less than 37% of people actually seek mental health treatment for their symptoms. Other common mental health conditions include depression, panic disorders, Post-Traumatic Stress Disorder (PTSD), Obsessive Compulsive Disorder (OCD), and eating disorders. The CDC estimates 1 in 5 experience at least one mental health condition every year [1]. Mental health is not static; it can shift at any time due to biological factors, life experiences, or a predisposition due to family history [21]. There are already ongoing studies about this issue and it is expected to see an increase of interest in the coming decade.

The federal and state governments are responsible for addressing mental health. The federal government is responsible for regulation, consumer protection, supplying funding for services and research. Since the federal government is a major funding source for mental health services, it establishes and enforces minimum standards for states to follow. States are free to expand beyond the standards set by the federal government [20]. The U.S. House of Representatives passed a $1.5 trillion spending package in March 2022 for Fiscal Year 22 (FY22) that includes investments to expand mental health care [22]. Specifically, $2.14 billion of the total amount was allocated to the National Institute for Mental Health (NIMH). This is a $37 million increase that includes $20 million to expand research on the impact of the COVID-19 pandemic on mental health. Currently there is research that explores the impact of COVID-19 on different groups like the general population, children, elderly, health care professionals, people with preexisting mental health conditions, people with no preexisting mental health conditions, people who were infected with COVID-19, and homeless or refugees [37]. While there is much research and discussion that exists already regarding mental health and the COVID-19 pandemic [13, 26, 27, 37], there is much left to be uncovered.

The COVID-19 pandemic was an unprecedented event that saw long periods of quarantine and social isolation. While social isolation and loneliness were an issue already, the COVID-19 pandemic only exasperated these problems. Preliminary surveys suggest that within the first month of COVID-19, loneliness increased by 20–30% while emotional distress tripled [13]. At the time of publication, Rajkumar [27] reported there were 720,000 cases and 33,000 confirmed deaths and this widespread outbreak is associated with negative mental health consequences. As of July 6, 2022, the World Health Organization (WHO) Coronavirus Dashboard reports 548,990,094 confirmed cases and 6,341,637 deaths worldwide [38]. This is a huge increase in the number of people impacted by the COVID-19 pandemic as well as the number of people who have potentially developed one or more mental health issues stemming from it. Rajkumar [27] suggested that symptoms of anxiety, depression, and self-reported stress are psychological reactions to the pandemic. Panchal et al. [26] reported an increase on various mental health issues like difficulty sleeping, difficulty eating, increases in alcohol consumption or substance use, and worsening chronic conditions due to worry and stress over the coronavirus.

Social media plays a large role in daily life. Devices with screens, such as computers and smartphones, are widely accessible to the general population. A rise in social media has taken place over the last few years in conjunction with this increased accessibility of devices. The COVID-19 pandemic increased the reliance on technology for daily tasks as well as communication with others through social media. Currently, there has been interest and research focus specifically on the impact of social media on children, adolescents, and young adults. The Department of Health and Human Services (HHS) announced in March 2022 nearly 35 million in funding to strengthen and expand mental health services and suicide prevention programs for America's children and young adults [31]. This announcement is part of a new Administration-wide initiative to tackle the nation's mental health crisis.

2 Current Research

The current research done regarding mental health and social media has been mostly from a psychology standpoint. There have been many publications that took data from social media sites or conducted self-reporting surveys to collect data regarding one or more mental health issues. Some studies analyzed this data to make observations regarding the connection between mental health and social media. Other researchers used this data in conjunction with various machine learning techniques to make predictions. A small subset used mathematical modeling techniques along with machine learning to make predictions. Depression and anxiety were the two most commonly studied risk factors in relation to mental health. According to Nesi [24], cyberbullying has been consistently associated with higher rates of suicidal behavior and self harm, which were the third and fourth most studied risk factors in this review, as well as internalizing and externalizing problems. A list of various risk factors can be found in Table 1.

2.1 Data Collection, Self-Reporting Surveys, and Reviews

As interest in mental health research has increased, there has been an increase in review studies as well. Naslund et al. [23] summarized challenges and benefits of social media and mental health by analyzing recent peer-reviewed publications from Medline and Google Scholar. The challenges were categorized as: (1) Impact on symptoms; (2) Facing hostile interactions; and (3) Consequences in daily life. The studies included in this review showed an increased risk of exposure to harm, social isolation, depressive symptoms, bullying, increased loneliness, worsening of mental health symptoms, cyberbullying, increased anxiety, risk of suicide, and privacy concerns. Karim et al. [15] categorized sixteen papers into two outcomes of mental health: anxiety and depression. The main risk factors for anxiety and depression found from the study were time spent, activity type, and addiction to social media.

79 studies focusing on adolescents ranging between 13 and 19 years of age were categorized by Schønning et al. [32] and it was found that depression was the most studied aspect and Facebook was the most studied social network site. From this review, about three-fourths of the studies focused on social media and an aspect of pathology and 94% of the papers in this study were quantitative. Meier and Reinecke [19] also found that depressive symptoms were the most common meta-analyzed indicator in internalizing psychopathology. This study also found that there may be a small negative association between social media and mental health, but results depend on various mental health indicators and computer-mediated-communication approaches. Findings by McCrae et al. [18] corroborated the finding of Schønning et al. [32], Meier and Reinecke [19] by concluding there may be a statistically significant correlation between social media use and depressive symptoms in young people. Chancellor and De Choudhury [6] also found that depression was the most studied symptom and suicidality was the second most studied symptom out of the 75 papers summarized that were published between 2013 and 2018. That literature review focuses on study design, methods, and research design of publications that predict mental health status using social media data. Almost all of the papers cited by [6] frame their contributions as predicting mental health and use algorithms from machine learning and statistical models. After evaluating 501 articles and using inclusion/exclusion criteria, Sadagheyani and Tatari [30] assessed 50 cases for their results regarding mental health and social media. Some negative effects were anxiety, depression, loneliness, poor sleep quality, poor mental health indicators, thoughts of self-harm and suicide, increased levels of psychological distress, cyberbullying, body image dissatisfaction, fear of missing out (FOMO), and decreased life satisfaction.

There have been numerous studies on mental health that involved self-reporting surveys. A large focus of surveys have targeted adolescent-aged persons [14, 25] or college-aged persons [3, 8, 11, 34]. O'Reilly et al. [25] surveyed adolescents ranging in age from 11 to 18 years and found they are concerned about the risks that social media has towards mental wellbeing. Three major findings were that social media was believed to cause mood and anxiety disorders for some adolescents, social media is a platform for cyberbullying, and social media is addicting. Jones et al. [14] used data from the 2021 Adolescent Behaviors Experiences Survey conducted by the CDC from January to June 2021. This survey assessed United States high school students' (grade 9–12) mental health and suicidality during the COVID-19 pandemic with a large sample size of 7,705 participants. This survey found that more than one in three high school students (37.1%) experienced poor mental health during the COVID-19 pandemic. For many students, mental health was impacted by remote learning, social isolation, financial and familial hardships, worry of illness, and reduced access to healthcare. Son et al. [34] studied the impact of COVID-19 on college students' mental health and wellbeing at Texas A&M University in the United States. It was found that 71% saw an increased level of stress and anxiety due to the pandemic. Stressors like fear and worry about health, difficulty in concentrating, disruptions to sleep patterns, decreased social interactions, and increased concerns regarding academics contributed to increased levels of stress, anxiety, and depression. Davila et al. [8] conducted an initial survey and followup survey with college-age young adults enrolled in an introductory psychology or abnormal psychology course at an unspecified university to establish if there was any relationship between social media and depression or rumination/co-rumination. It was found that depressive symptoms were associated with quality, and not quantity, of the social networking interactions. Some evidence suggested that depressive rumination and co-rumination impacted social networking usage and quality. In a similar research direction, Feinstein et al. [11] surveyed students at Stony Brook University in the United States to test a model whether negative social comparisons on Facebook put individuals at risk for rumination and depressive symptoms. The results of this model concluded that this is true and contributes to linking social networking use to negative mental health outcomes. A survey was conducted at an unnamed university in the south-eastern region of the United States by Berryman et al. [3] and it examined time spent on social media, importance of social media, and tendencies to engage in vaguebooking. Factors considered were general mental health symptoms, suicide ideation, loneliness, social anxiety and decreased empathy. There were also regression analyses carried out for total mental health symptoms, suicidal thoughts, social anxiety, loneliness, and general anxiety. The results from this study indicated that social media use was not predictive of negative mental health, but vaguebooking was predictive of suicidal ideation.

2.2 *Data Collection with Machine Learning Applications*

Studying mental health using machine learning has allowed for classifying content being posted as well as making various types of predictions. The data utilized in these studies came from social media sites like Reddit [10, 12, 29, 36], Twitter [9, 28], and Instagram [17] as well as from self-reporting surveys [35]. It is expected to see more publications using these and other techniques in the coming years. A summary of the machine learning techniques can be found in Table 2 and a list of the platforms studied or where data was gathered from can be found in Table 3.

Using data directly from the social media sites studied allows researchers to train and obtain more accurate classification algorithms. Gkotsis et al. [12], De Choudhury et al. [10], and Thorstad and Wolff [36] used public data from Reddit to recognize and classify mental illness posts. Using a neural network and deep learning approach, Gkotsis et al. [12] was able to automatically recognize a mental illness post with an accuracy of 91.08% and select the correct theme with a weighted accuracy average of 71.37%. De Choudhury et al. [10] was able to classify content from Reddit into categories of mental health concern or suicide ideation. A machine learning prediction framework was made specifically to see if users would go from the MentalHealth to SuicideWatch subreddit by looking at linguistic structure, interpersonal awareness, and interaction categories. By taking language samples from Reddit and analyzing posts on mental illness subreddits and non-clinical subreddits, Thorstad and Wolff [36] was able to use an L2-penalized logistic regression model to train a program to distinguish different mental illnesses like Attention-Deficit/Hyperactivity Disor-

Table 1 Risk factors studied

Factors	Source(s)
Depression	Gkotsis et al. [12], Meier and Reinecke [19], De Choudhury et al. [10], Reece et al. [28], Davila et al. [8], Sadagheyani and Tatari [30], O'Reilly et al. [25], Bagroy et al. [2], Chancellor and De Choudhury [6], Manikonda and De Choudhury [17], Feinstein et al. [11], De Choudhury et al. [9] Thorstad and Wolff [36], McCrae et al. [18], Braghieri et al. [4], Naslund et al. [23], Karim et al. [15], Berryman et al. [3], Schønning et al. [32], Kim [16], Nesi [24], Richter et al. [29], Jones et al. [14], Son et al. [34]
Anxiety	Gkotsis et al. [12], Meier and Reinecke [19], Sadagheyani and Tatari [30], O'Reilly et al. [25], Chancellor and De Choudhury [6], Manikonda and De Choudhury [17], Thorstad and Wolff [36], Naslund et al. [23], Karim et al. [15], Berryman et al. [3], Schønning et al. [32], Kim [16], Richter et al. [29], Jones et al. [14], Son et al. [34], Bagroy et al. [2]
Suicide or suicide ideation	Gkotsis et al. [12], De Choudhury et al. [10], Sadagheyani and Tatari [30], O'Reilly et al. [25], Chancellor and De Choudhury [6], Manikonda and De Choudhury [17], Naslund et al. [23], Berryman et al. [3], Kim [16], Nesi [24], Jones et al. [14], Son et al. [34], Bagroy et al. [2]
Self harm	Gkotsis et al. [12], Sadagheyani and Tatari [30], Chancellor and De Choudhury [6], Manikonda and De Choudhury [17], Schønning et al. [32], Nesi [24], Bagroy et al. [2]
Cyberbullying	Sadagheyani and Tatari [30], O'Reilly et al. [25] Naslund et al. [23], Schønning et al. [32], Kim [16], Nesi [24]
Eating disorders	De Choudhury et al. [10], Son et al. [34], Chancellor and De Choudhury [6], Manikonda and De Choudhury [17], Schønning et al. [32], Nesi [24]
Stress	Meier and Reinecke [19], O'Reilly et al. [25], Chancellor and De Choudhury [6] Jones et al. [14], Son et al. [34], Bagroy et al. [2]

Table 1 (continued)

Factors	Source(s)
Bipolar disorder	Gkotsis et al. [12], De Choudhury et al. [10], Chancellor and De Choudhury [6], Manikonda and De Choudhury [17], Thorstad and Wolff [36], Bagroy et al. [2]
Loneliness	Meier and Reinecke [19], Sadagheyani and Tatari [30], Naslund et al. [23], Berryman et al. [3], Kim [16]
Schizophrenia	Gkotsis et al. [12], Naslund et al. [23], Chancellor and De Choudhury [6], Manikonda and De Choudhury [17],
Body image disorders	Meier and Reinecke [19], Nesi [24] Sadagheyani and Tatari [30], Schønning et al. [32]
Post-traumatic stress disorder (PTSD)	Reece et al. [28], Bagroy et al. [2], Chancellor and De Choudhury [6], Manikonda and De Choudhury [17]
Sleep or poor sleep quality	Sadagheyani and Tatari [30], Schønning et al. [32] Nesi [24], Son et al. [34]
Addiction	Gkotsis et al. [12], De Choudhury et al. [10], O'Reilly et al. [25]
Self-esteem	De Choudhury et al. [10], O'Reilly et al. [25], Schønning et al. [32]
Severe or stigmatized illness	De Choudhury et al. [10], Chancellor and De Choudhury [6]
Rumination/co-rumination	Davila et al. [8], Feinstein et al. [11], Richter et al. [29]
Alcoholism or alcohol use	Gkotsis et al. [12], Schønning et al. [32]
Fear of missing out (FOMO)	Sadagheyani and Tatari [30], Schønning et al. [32]
Borderline personality disorder (BPD)	De Choudhury et al. [10], Chancellor and De Choudhury [6]
Panic attacks	Chancellor and De Choudhury [6], Manikonda and De Choudhury [17]

der (ADHD), anxiety, bipolar disorder, and depression. Twitter data of users who reported being diagnosed with clinical depression was used by De Choudhury et al. [9]. Through these users' previous postings over a year preceding the depression diagnosis various aspects were studied. It was found that by using different cues

Table 1 (continued)

Factors	Source(s)
Drug use or substance abuse	Schønning et al. [32], Kim [16]
Worry	Richter et al. [29], Son et al. [34]
Opiates	Gkotsis et al. [12]
Autism	Gkotsis et al. [12]
Hopelessness	De Choudhury et al. [10]
Impulsiveness	De Choudhury et al. [10]
Psychological distress	Sadagheyani and Tatari [30]
Decreased life satisfaction	Sadagheyani and Tatari [30]
Obsessive-compulsive disorder (OCD)	Manikonda and De Choudhury [17]
Attention-deficit/hyperactivity Disorder (ADHD)	Thorstad and Wolff [36]
Decreased empathy	Berryman et al. [3]
Somatization	Berryman et al. [3]
Vaguebooking	Berryman et al. [3]
Internalizing or externalizing problems	Nesi [24]
Social exclusion	Nesi [24]
Concentration issues	Son et al. [34]

from social media like engagement level, emotion, language styles, and mentions of antidepressants, one could see useful signals for characterizing the onset of depression in individuals. Supervised learning, principal component analysis (PCA), and support vector machines (SVM) were used to train a model to predict depression. This was seen through decreases in social activity, raised negative affect, and increased relational and medicinal concerns. Manikonda and De Choudhury [17] did a quantitative analysis of images shared on Instagram regarding a variety of mental health issues using automated computer vision techniques and clustering. It was found that people are using Instagram to express discontent around mental health issues, seek support, and disclose information about their emotional distress.

Predictions made using machine learning allow researchers to obtain more accuracy and possibly new insights. Srividya et al. [35] applied several machine learning algorithms like SVM, decision trees, naïve Bayes classifier, K-nearest neighbor classifier, and logistic regression to identify the state of mental health and predict the onset of mental illness in a target group of two different age ranges of 18–21 and 22–26 years old. The initial responses from the target groups were from a questionnaire and a clustering technique was applied and validated to build classifiers to predict the mental health of a person. Advanced machine learning techniques developed by Richter et al. [29] were used to analyze the results of a comprehensive behavioral test battery that detected and quantified cognitive emotional biases. The bagged decision tree classification algorithm had an accuracy of 71.44% for predicting symptomatic patients with high depression, anxiety, or both, and had an accuracy of 70.78% for

Table 2 Machine learning techniques utilized

Source	Technique(s)
Bagroy et al. [2]	Random forests, ada boost, logistic regression, support vector machines (SVM)
Berryman et al. [3]	Regression analysis
Braghieri et al. [4]	Regression analysis
Chancellor and De Choudhury [6]	SVM, logistic regression, feature engineering, random forests, decision trees, deep learning
De Choudhury et al. [9]	Principal component analysis (PCA), SVM supervised learning
Manikonda and De Choudhury [17]	Automated computer vision techniques, clustering
Gkotsis et al. [12]	Deep learning, neural network (NN), convoluted neural network (CNN), SVM
Reece et al. [28]	Random forest, feature extraction, time series analysis
Richter et al. [29]	Random forest, bagged decision tree classification
Srividya et al. [35]	SVM, decision trees, Naïve Bayes classifier, K-nearest neighbor classifier, logistic regression, Density based clustering, bagging, DBSCAN
Thorstad and Wolff [36]	Logistic regression model, clustering analysis, DBSCAN

the non-symptomatic control group of patients. The prediction algorithm had an accuracy of 68.07% in predicting participants with high depression and an accuracy of 74.18% in predicting participants with high anxiety. Computational models were created by Reece et al. [28] using Twitter data and depression history to predict the onset of depression and PTSD. Supervised learning algorithms extracted predictive features measuring affect, linguistic style, and context. These models successfully distinguished between depressed and healthy content. This same process was applied to people with PTSD. The results were consistent even before a diagnosis of depression was issued and a state-space temporal analysis suggests that depression may be predicted from Twitter data several months before a diagnosis. The overall findings strongly support the claim that computational methods can effectively screen Twitter data for indicators of depression and PTSD.

Table 3 Social media platforms data gathered from or studied

Platform	Source(s)
Twitter	Reece et al. [28], Chancellor and De Choudhury [6] De Choudhury et al. [9], McCrae et al. [18], Naslund et al. [23] Karim et al. [15], Schønning et al. [32], Meier and Reinecke [19]
Facebook	Chancellor and De Choudhury [6], McCrae et al. [18], Braghieri et al. [4], Karim et al. [15], Schønning et al. [32] Meier and Reinecke [19]
Reddit	Bagroy et al. [2], Gkotsis et al. [12], De Choudhury et al. [10], Reece et al. [28], Chancellor and De Choudhury [6], Thorstad and Wolff [36],
Instagram	Chancellor and De Choudhury [6], Manikonda and De Choudhury [17], Karim et al. [15], Schønning et al. [32], Meier and Reinecke [19]
Snapchat	McCrae et al. [18], Karim et al. [15], Schønning et al. [32], Meier and Reinecke [19]
WhatsApp	McCrae et al. [18], Schønning et al. [32], Meier and Reinecke [19]
Tumblr	Chancellor and De Choudhury [6], Schønning et al. [32]
MySpace	McCrae et al. [18], Schønning et al. [32]
Youtube	Naslund et al. [23], Schønning et al. [32]
Linkedin	Karim et al. [15]
Skype	Schønning et al. [32]
Weibo	Chancellor and De Choudhury [6]
Reachout	Chancellor and De Choudhury [6]
LiveJournal	Chancellor and De Choudhury [6]
Mixi	Chancellor and De Choudhury [6]
TOYBO	Chancellor and De Choudhury [6]
PTT	Chancellor and De Choudhury [6]
Flickr	Chancellor and De Choudhury [6]
Ping	Schønning et al. [32]
Bebo	Schønning et al. [32]
Hyves	Schønning et al. [32]
Kik	Schønning et al. [32]
Ask	Schønning et al. [32]
Qzone	Schønning et al. [32]

2.3 Modeling of Mental Health Using Survey Data and Machine Learning

There are published studies that use survey data in conjunction with machine learning techniques to formulate mathematical models regarding mental health. This category is smaller as of the writing of this review, but it is expected to see more discussions and publications in the coming years. Kim [16] used data from the Korean Youth Panel Survey to create hierarchical linear models that are estimated to probe the psychological effects of time spent online. This analysis, which was associated with self-reported mental problems and suicidal thoughts, showed that online social networking is negatively associated with the psychological status of Korean students. Again targeting college-age persons, using data from Reddit, Bagroy et al. [2] created a Mental Wellbeing Index (MWI) to evaluate the mental status of over 100 universities in the United States. The relationship between various attributes of the universities and the MWI were shown using machine learning. The actual factors being predicted in this model with 97% accuracy can be found in Table 1. Braghieri et al. [4] looked at when Facebook was introduced at 775 colleges in the United States in conjunction with seventeen successive reports from the National College Health Assessment (NCHA) survey at the time of Facebook's expansion. A two-way fixed-effect (TWFE) was estimated as a baseline. This equation was then expanded upon to model other factors. An event study-version estimation of the model with distance to and from the introduction to Facebook was created. To estimate the effects of the exposure length of Facebook, an intensity level equation was formulated. Some major findings from this study were that the introduction of Facebook at a college increased symptoms of poor mental health (especially depression), students who were susceptible to mental illness used mental healthcare services more, and after Facebook's introduction in conjunction with poor mental health, academic performance suffered. These findings corroborate the hypothesis that social media has had a negative impact on mental health of teenagers and young adults.

3 Concluding Remarks

This review summarizes some of the current research published regarding mental health and social media. Most research is either inconclusive, suggests that there may be small negative correlations, or that there is no correlation at all between mental health and social media. Further research is needed on this subject and there is expected to be a significant amount in the next 10–20 years. Social media as a whole has positive and negative aspects, which are addressed in some of these studies and published papers [23, 24, 30]. Which platforms are popular is always changing and so are the mental challenges people face. That means the impact of social media is also changing over time. This research is interesting and important as the mental health crisis has been continuously worsening.

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