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Analysis Of Social Media and Sleep Disorders on Mental Health

DAB422 CAPSTONE PROJECT

SUBMITTED TO PROF. ADEGOKE OJENIYI

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## **Introduction**

In the last ten years social networks have become an essential part of people’s lives especially youths and young adults. Even though these technologies provide novel opportunities for social interaction and individual identity, their constant use has been associated with many health consequences. More specifically, the social media usage, sleep patterns, and mental health are interconnected in various ways, which are detailed next. (Yu, (2024))   
The purpose of this current research proposal is to assess the existing literature and examine the correlation between the use of social media and sleep and mental health consequences. They will analyse and compare frequency, duration, and timing of social media use and presence of sleep disorders. The findings of this report will seek to discuss how sleep disruptions caused by social media can influence mental disorders such as anxiety and depression. Furthermore, we shall assess the effectiveness of interventions to reduce the social media usage at night to enhance sleep and mental health.  
It is important to comprehend these complex relations because sleep and mental health are two interrelated components of a human’s health. Stress has been known to worsen mental health conditions and mental health disorders play a role in sleep disorders. The use of social media further complicates this relationship.  
In doing so, it aims to foster a better understanding of and guide practice and policy in relation to healthier social media use and sleep and mental health, especially for youth. The next sections of the work will present the background information concerning the given topic, describe the methods used during this study, state the main results of the investigation, discuss the ongoing issues that are crucial for this field of research and suggest possible further developments. (Cain & Gradisar, 2010)

A person sleeping at a desk with a computer

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Figure 1 Digital Exhaustion: The Toll of Social Media on Sleep and Mental Health

**1.1 Background of the study**

Today, social media has taken over the way people interact and communicate in their day-to-day basis especially among the youth. Social sites such as Face book, Instagram, snapchat and twitter have become almost a necessity in the lives of many individuals in the last ten years. The penetration of social media into the daily lives of individuals has not only changed social behaviours but also influenced different spheres of human health starting with psychological and including the amount and quality of sleep.

Social media is full of content and every user’s constant companion and entertainment, and that is why people stay online and active in the wee hours. Research that links the time children spend on digital platforms and screens before they sleep is damaging their circadian rhythm; a natural timer that is responsible for controlling the rhythm sleep. This disruption is related to decrease in sleep quality and decrease in quantity of sleep which has serious consequences for mental condition. (Yu, (2024))

The relationship between social media use and sleep disorders and mental health is not fully understood. In one perspective, people can use the SNS to escape from the stress experienced throughout the day since it’s an easy way of diverting their attention. On the other hand, late night social media activities are likely to make a cycle; since poor sleep is likely to lead to anxiety, depression and increase the tendency of engaging in social media more often.

New approaches are now used to investigate situational characteristics of social media uses with reference to the social, emotional and cognitive perspectives rather than have a generalized view of quantized Time on Device. This shift further acknowledges that necessary changes exist beyond the literature convenience argument which social media brings this aspect through altering the people’s interaction. (Scott & Cleland Woods, 2019)

**1.2 Statement of the Problem**

Increased use of social media, especially among youths and young adults, have raised some issues about the effects this has on sleep and mental health. Research has it that many teenage persons get less than the required eight hours of sleep at night and this is attributed to time spent on social media sites. (Yu, (2024)).This raises concern and requires a determination of the first and second-order effects in response to this behaviour.

Logarithmic sleep disorders for example, insomnia is socially manifested in the current youth population due to late night social media activity. Besides, lack of sleep quality has also been directly associated with the emergence of psychological disorders such as depression and anxiety. Despite the growing body of evidence, there remains a lack of comprehensive studies that fully explore the bidirectional nature of this relationship: Is that to mean that the use of social media leads to poor sleep or is it just a section of the population who are already experiencing sleep difficulties get addicted to social media as a way of compensating for their sleepless nights? (Seabrook, 2016)

The sleep and mental health research literatures have made recent advances towards a more nuanced understanding of social media use: shift from the traditional emphasis of the ‘time spent’ in using online media to understanding content, context and experiences of interactions. (Scott & Cleland Woods, 2019). However, the researchers in these fields have been constrained by the available research measures. Prominent features include the application of single-item, non-validated measures, often reflecting duration or frequency of use, while existing, multi-items validated measures are lacking in generalizability and risk entailing pathologization of social media use. (Seabrook, 2016)

**1.3 Study Aim and Objectives**

This study aims to investigate the complex relationships between social media use, sleep disorders, and mental health, with a particular focus on adolescents and young adults.

The specific objectives of the study are:

1. To analyse the correlation between the frequency and duration of social media use and the prevalence of sleep disorders.
2. To examine how sleep disruptions, attributed to social media use, impact mental health outcomes such as anxiety and depression. (run)
3. To explore the effectiveness of interventions that target reductions in social media use, particularly at night, in improving sleep quality and mental well-being.
4. To develop a more nuanced understanding of the social, emotional and cognitive aspects of social media engagement and their implications for both sleep and mental health.
5. To evaluate existing measurement tools for social media use and develop improved measures that capture relevant experiences beyond just frequency and duration of use.
6. To compare the performance of different machine learning models (k-means, RNN, CNN, and NLP) in predicting and analysing the relationships between social media use, sleep disorders, and mental health outcomes.

**1.4 Study Questions and/or Hypotheses**

The following research questions guide this study:

1. How do technology usage hours (social media, gaming, screen time) affect sleep patterns and quality?
2. How What is the relationship between technology usage and mental health status, particularly stress levels?
3. Does the availability of support systems (online or offline) play a role in mitigating the negative effects of technology overuse on mental health?
4. How do physical activity levels and work environment impact the relationship between screen time and mental health outcomes?
5. How do the content, context and quality of social media interactions relate to sleep and mental health outcomes?
6. What are the underlying motivations and experiences driving nighttime social media use despite potential sleep costs?
7. How can we determine the average daily social media usage time among young adults in the sample, and how does it compare to their overall screen time? [Descriptive Analysis] (Cain & Gradisar, 2010)
8. How can we estimate the likelihood of experiencing high stress levels given an individual's technology usage patterns and work environment impact?
9. How does the combination of high social media usage and low sleep hours correlate with poor mental health status? [Diagnostic Analysis] (Seabrook, 2016)
10. How can a machine learning model accurately predict an individual's stress level based on their technology usage patterns, sleep hours, and physical activity? [Predictive Analysis]
11. How can we determine the optimal balance of reduced social media usage and increased physical activity to improve mental health outcomes and sleep quality for young adults? [Prescriptive Analysis]

**1.5 Significance of the Study**

This study is significant for several reasons:

1. It addresses an urgent public health issue: the growing impact of social media use on the mental and physical well-being of adolescents and young adults. As social media continues to play a central role in the lives of young people, understanding its effects on sleep and mental health becomes increasingly critical.
2. The findings have the potential to inform public health campaigns and interventions designed to promote healthier social media habits. By identifying key patterns in social media usage that contribute to poor sleep and mental health outcomes, this research can guide the development of evidence-based strategies aimed at improving sleep hygiene among young people.
3. It contributes to the academic literature by providing insights into the mechanisms through which social media use affects mental health and sleep quality. These insights will be valuable for future research and may lead to the development of more comprehensive intervention programs.
4. The study moves beyond simplistic measures of screen time to examine the nuanced social, emotional and cognitive aspects of social media engagement. This more holistic approach can inform a deeper understanding of how social media use relates to overall health and well-being.
5. By developing improved measurement tools, the study can enhance the quality and relevance of future research in this rapidly evolving field. (Scott & Cleland Woods, 2019)
6. The findings can help clinicians, educators, and parents better understand and address the complex relationships between social media use, sleep, and mental health in young people. (Scott & Cleland Woods, 2019)

**1.6 Scope of the Study**

1. Population: The target audiences were those of the age 15-30 years as most of them are socially active especially on social media platforms up to 90 years.
2. undefined social media platforms: Some of the famous social media platforms are Facebook, Instagram, Snapchat, and Twitter among others.
3. undefined Sleep measures: Subjective information about the quality, duration, and disorders of sleep, combined with objective data where available.
4. undefined Mental health outcomes: Self-rated questionnaires that assess the level of anxiety, depression, stress, and general wellness.
5. Social media use measures: Frequency and duration of use, timing of use (particularly nighttime use), content and quality of interactions, motivations for use, and emotional connection to platforms.
6. Contextual factors: Physical activity levels, work/school environment, availability of support systems.
7. Timeframe: Cross-sectional data collection, with recommendations for future longitudinal studies.

While the study is limited to a specific age group and relies on both subjective and objective data, it provides critical insights into the relationship between social media usage, sleep disturbances, and mental health. Future research could expand on this by exploring other age groups and investigating long-term effects.

**1.7 Operational Definition of Terms**

1. Technology Usage Hours: The total hours spent engaging with various forms of technology, including social media, gaming, and screen-based activities.
2. Social Media Usage Hours: The specific time spent on social media platforms, such as Facebook, Instagram, and Twitter.
3. Gaming Hours: The amount of time spent on video games across different platforms.
4. Screen Time Hours: The cumulative time spent on screens for work, entertainment, or leisure purposes.
5. Mental Health Status: A measure of psychological well-being, including indicators of anxiety, depression, and emotional stability.
6. Stress Level: Self-reported or measured levels of psychological or emotional stress.
7. Sleep Hours: The number of hours an individual sleeps in a typical 24-hour period.
8. Physical Activity Hours: The amount of time spent engaging in physical exercise or activity.
9. Support Systems Access: The availability of social, familial, or online support structures to aid in mental and emotional health.
10. Work Environment Impact: The effect of an individual's work environment on their mental health and well-being.
11. Social Media Engagement: The nature and quality of interactions on social media platforms, including content shared, responses received, and emotional reactions.
12. Nighttime Social Media Use: Engagement with social media platforms during typical sleeping hours or immediately before bedtime.
13. Sleep Quality: A measure of how well an individual sleeps, including factors like ease of falling asleep, number of awakenings, and feeling rested upon waking.

These operational definitions have been developed out of the variables that are identified in the two datasets used in this study. They clearly specify how each variable is defined and measures when discussing the effects of social media use, sleep, and mental health. It is by combining data from both sources that this project will be able to present a better and more elaborate view of the correlations between these variables.

1. **Introduction**
   1. Defining Social Media, Sleep Disorders, and Mental Health

Social Media

[Social media](https://www.techtarget.com/whatis/definition/social-media) refers to internet-based applications and platforms that allow users to create, share, and exchange content, as well as participate in social networking. (Karaman, 2024)

These platforms facilitate the creation and sharing of information, ideas, interests, and other forms of expression through virtual communities and networks. Social media platforms are characterized by several key features, including user-generated content, user profiles, social connections and networks between users, interactive participation and engagement, and real-time updates and communication. Users create and share their own content, such as photos, videos, and posts, and each user has a profile that displays their personal information, interests, and activity. These platforms allow users to connect with friends, family, and other users, forming networks of relationships. Additionally, users can like, comment, share, and interact with content and other users, fostering a high level of engagement. Real-time updates and instant messaging capabilities enable immediate communication and information sharing. Common examples of social media platforms include Facebook, Instagram, Twitter, LinkedIn, YouTube, and TikTok. The defining characteristic of social media is the ability for users to both consume and produce content, leading to the term "prosumers." (Karaman, 2024)

Common features of social media platforms include user-generated content, user profiles, and the ability to connect with others. Popular examples include Facebook, Instagram, Twitter, and TikTok. A recent survey in Turkey reported that approximately 91% of people aged 16-24 years were internet users, with social networks being the most common purpose at 84.1% (Karaman, 2024)

Sleep Disorders

Sleep disorders are conditions that impair the normal sleep-wake cycle, affecting the quality, timing, and amount of sleep an individual gets. ((2018))The International Classification of Sleep Disorders (ICSD-3) categorizes sleep disorders into six major categories: insomnia, sleep-related breathing disorders, central disorders of hypersomnolence, circadian rhythm sleep-wake disorders, parasomnias, and sleep-related movement disorders (American Academy of Sleep Medicine, 2014). Insomnia involves difficulty falling or staying asleep, while sleep-related breathing disorders, such as obstructive sleep apnea, involve abnormal breathing patterns during sleep. Central disorders of hypersomnolence, including narcolepsy, are characterized by excessive daytime sleepiness. Circadian rhythm sleep-wake disorders occur when there is a misalignment between an individual's internal clock and the external environment. Parasomnias include abnormal behaviours or experiences during sleep, such as sleepwalking or night terrors. Lastly, sleep-related movement disorders, like restless legs syndrome, involve abnormal movements that disrupt sleep.

Common sleep disorders include insomnia (difficulty falling or staying asleep), sleep apnea (pauses in breathing during sleep), restless legs syndrome, and narcolepsy (National Institute of Neurological Disorders and Stroke, 2019). Sleep disorders can have significant impacts on physical health, mental wellbeing, and overall quality of life.

Mental Health

The World Health Organization (2018) defines mental health as "a state of well-being in which an individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and is able to make a contribution to his or her community". Mental health encompasses emotional, psychological, and social well-being, affecting how individuals think, feel, and act (U.S. Department of Health and Human Services, 2020).

Mental health exists on a continuum, ranging from mental wellness to mental illness. Mental illnesses are health conditions involving changes in emotion, thinking, or behaviour (or a combination of these) that are associated with distress and/or problems functioning in social, work, or family activities (American Psychiatric Association, 2018).

Common mental health disorders include depression, anxiety disorders, bipolar disorder, schizophrenia, eating disorders, and substance use disorders. Depression is characterized by persistent feelings of sadness and loss of interest in activities. Anxiety disorders involve excessive fear or worry, while bipolar disorder includes episodes of both mania and depression. Schizophrenia is a severe mental disorder that affects thinking, feeling, and behaviour. Eating disorders, such as anorexia nervosa and bulimia nervosa, involve preoccupation with food, body weight, and shape. Substance use disorders occur when the recurrent use of alcohol or drugs causes significant impairment, such as health problems or failure to meet major responsibilities at work, school, or home.

It's important to note that mental health is not merely the absence of mental illness, but also includes positive aspects of psychological functioning and wellbeing (Keyes, 2005).

* 1. History of Social Media, Sleep Disorders, and Mental Health Research

*Evolution of Social Media Platforms*

The history of social media can be traced back to the early days of the internet, with each decade bringing new innovations and platforms. In the 1970s and 1980s, early online communication began with the first email sent between computers in 1971. This was followed by the introduction of Bulletin Board Systems (BBS) in 1978, which allowed users to communicate and share files. By 1988, Internet Relay Chat (IRC) enabled real-time chat, laying the groundwork for future social interactions online.

The 1990s marked the birth of social networking sites. In 1997, Six Degrees launched as one of the first recognizable social networking sites, allowing users to create profiles and connect with friends. This era also saw the rise of personal blogging platforms like LiveJournal and Blogger in 1999, which popularized the concept of sharing personal thoughts and experiences online. The early 2000s witnessed the rise of major platforms, with Friendster launching in 2002 and quickly gaining over 3 million users. Myspace followed in 2003, becoming the most popular social networking site globally. In 2004, Facebook was launched, initially targeting college students, and in 2006, Twitter introduced the concept of microblogging. <https://blog.hubspot.com/marketing/social-media-history>

The 2010s saw mobile and visual platforms dominate the social media landscape. Instagram, launched in 2010, focused on photo-sharing and quickly gained popularity. Snapchat, introduced in 2011, brought ephemeral messaging to the forefront, allowing users to send disappearing messages. In 2016, TikTok (originally Musical.ly) gained popularity with its short-form video content. The 2020s have brought emerging trends such as virtual and augmented reality social platforms like Meta’s Horizon Worlds and decentralized social networks based on blockchain technology. These advancements reflect the continuous innovation in social media, aiming to enhance user experience while addressing the challenges of privacy and data security.

*Development of Sleep Disorder Research*

The field of sleep disorder research has evolved significantly over the past century, beginning with foundational studies in the 1920s and 1930s. In 1924, Hans Berger recorded the first human electroencephalogram (EEG), marking a pivotal moment in understanding brain activity during sleep. Nathaniel Kleinman, often referred to as the father of modern sleep research, began systematic studies of sleep and wakefulness in 1929. The discovery of sleep stages and REM sleep in the 1950s and 1960s, particularly the work of Eugene Asterisk and Kleinman in 1953, further advanced the field. By 1968, the first polysomnography recording, which combined EEG, EOG, and EMG, was conducted, providing a comprehensive method to study sleep patterns.

The 1970s marked the establishment of sleep medicine as a distinct field. The first sleep research society was founded in 1970, and in 1975, the first sleep disorders centre was established at Stanford University. This period also saw the recognition and classification of sleep disorders, with the publication of the first International Classification of Sleep Disorders (ICSD) in 1979. The discovery of the role of orexin/hypocretin in narcolepsy in 1989 was another significant milestone, shedding light on the mechanisms underlying this sleep disorder.

From the 2000s to the present, advances in genetic and neuroimaging studies have provided deeper insights into the mechanisms of sleep disorders. New treatments have been developed, including cognitive behavioural therapy for insomnia (CBT-I), which has become a widely accepted non-pharmacological treatment. There is also a growing recognition of the importance of sleep health in overall wellbeing, leading to increased public awareness and research funding. (By Dr. Liji Thomas, 2022)

*Progression of Mental Health Studies*

The study of mental health has a long and complex history, with significant shifts in understanding and approaches over time. In ancient times, mental illness was often attributed to supernatural causes, with treatments ranging from exorcisms to trephination. Hippocrates (460-370 BCE) was one of the first to propose that mental disorders had physical causes, laying the groundwork for a more scientific approach. The establishment of Bethlem Royal Hospital in London in 1247 marked the beginning of institutional care for mental illness.

The 19th century saw the emergence of psychiatry as a distinct medical field. Johann Christian Reil coined the term “psychiatry” in 1808, and the Association of Medical Superintendents of American Institutions for the Insane, the precursor to the American Psychiatric Association, was founded in 1844. Wilhelm Wundt established the first experimental psychology lab in 1879, further advancing the scientific study of mental health. The early 20th century brought the development of psychoanalysis by Sigmund Freud and the rise of behaviourism, marked by John B. Watson’s 1913 publication “Psychology as the Behaviourist Views It.”. (Seabrook, 2016)

The mid-20th century saw significant advancements in biological psychiatry and the deinstitutionalization movement. The first Diagnostic and Statistical Manual of Mental Disorders (DSM) was published in 1952, providing a standardized classification system for mental disorders. The introduction of the first antipsychotic medication, chlorpromazine, in 1954 revolutionized the treatment of mental illness. The Community Mental Health Act of 1963 in the US promoted deinstitutionalization, shifting the focus to community-based care.

From the late 20th century to the present, there has been a growing emphasis on integrative approaches and neuroscience. Evidence-based treatments have become the standard, and the development of neuroimaging techniques has provided new insights into brain function. There is an increased focus on prevention, early intervention, and mental health promotion, recognizing the role of social determinants in mental health. [This holistic approach considers biological, psychological, and social factors, reflecting the complexity of mental health and illness4](https://publichealth.jhu.edu/departments/mental-health/about/origins-of-mental-health)[5](https://www.nih.gov/about-nih/what-we-do/nih-almanac/national-institute-mental-health-nimh)[6](https://www.healthyplace.com/other-info/mental-illness-overview/the-history-of-mental-illness)[7](https://brainspallc.com/blog/understanding-mental-health-from-historical-perspective/).

* 1. Previous Studies on Social Media, Sleep Disorders, and Mental Health

*Social Media Use and Global Health*

The famous American editor and publisher Elbert Hubbard stated, ‘If you have health, you probably will be happy, and if you have health and happiness, you have all the wealth you need, even if it is not all you want.’ Health may be the most important topic in humans’ life. In the current study, health was approached as a general perspective. Global health includes both physical and mental health states (Davis, Balkin, and Juhnke, 2014). Studies showed that health was correlated with internet addiction (Chern and Huang, 2018), digital media use (Orzech et al., 2016), and social media or social networking sites (Bullen’s and VandenBosch, 2016; Rae and Lomborg, 2015) among emerging adults. This literature showed that the interaction between young adults and computers could be problematic. In a study, Sicilia and Charoensukmongkol (2015) stated participants who were addicted to social media tended to have lower mindfulness and higher emotional exhaustion. Mindfulness is related to one’s attention to the present moment, and lack of mindfulness can affect well-being, mental clarity, and academic achievement (Lin and Mai, 2018). Emotional exhaustion is related to burnout and causes people to feel lack of energy (Sicilia and Charoensukmongkol, 2015). As seen here, addictive social media use has both direct and indirect effects on health and its consequences.

*Social Media Use and Mental health*

In the literature of computers and human behaviour, one of the most investigated subjects is the relationship between computer use (digital media, social media, and internet) and depression. Depression is a common medical illness that negatively affects how people feel and act, and the way they think (American Psychiatric Association n.d.). A recent survey in the United States (U.S.) reported that emerging adults aged 18–25 years had the highest percentage of depression (13%) when compared to all U.S. adults (7.1%; National Institute of Mental Health 2017). Therefore, it is one of the reasons why it is investigated among emerging adults more than the other groups.

Although recent studies ( (Ahmad, 2017), (Appel, 2016) Belichick, Eickhoff, and Moreno, 2013; (Jasso-Medrano, J. L., & López-Rosales, F. , 2018)(Lin, 2018) (Balcı, 2018; Bilgin) is and Prinstein, 2015; Primack et al., 2017; Steers, 2016; Tandoc et al., 2015) investigated the associations between depression and social media use, there is no consensus that depression is an effect or a cause of internet and social media use (Balcı and Balogun, 2018; Blachnio, Przepiorka, and Panic, 2015). (Lin, 2018)conducted a study with 1718 U.S. emerging adults and found that social media use was correlated with increased depression. In another study, Ahmad et al. (2018) found similar results stating the students who spent more time on social media had more depression. On the other hand, Jasso-Medrano and López-Rosales (2018) investigated the relationship between social media use and addictive behaviour and depression and suicide ideation among Mexican university students. The results indicated that there was no significant relationship between social media use and depression. Similar to this, Elenchid et al. (2013) conducted a study with older adolescents and stated that there was no significant relationship between social media use and depression.

*Social Media Use and Sleep Disturbance*

Sleep is an important component for a healthy life, college success, and mood in university students. The New York Times personal health columnist Brody (2018) stressed out that sleep quality and sleep quantity was a key factor predicting grades and a student’s chance of graduating. Sleep disturbance refers to the quality and amount of quantity based on sleep patterns or interruption (Davis et al., 2014; Karaman, Balkin, and Juhnke, 2018). Sleep problems can be serious. Studies showed that college students who had sleep disorders had lower academic grades (Gaultney, 2010), lower academic performance and attention (Pagel, Forister, and Kwiatkowski, 2007), depression (Carney, Edinger, Meyer, Lindman, and Istre, 2006), and poorer health (Smaldone, Honig, and Byrne, 2007).

The literature (Genes, Akbıyık, Aypak, and Grovelingly, 2018; Woods and Scott, 2016; van der Schuur, Baumgartner, and Sumter, 2018; van der Velden, Setti, van der Mullen, and Das, 2019) examined the associations between social media use and sleep problems in recent years. Although researchers used different terms (e.g., social networking sites’ use, social media addiction, social media use) when referring to the social media usage, they mainly stressed ‘social media use’.

In a recent study, Genes (2018) examined the relationship between social media dependency and sleep quality among 16–19 years old high school students. In the study, authors only added Facebook as social media site. The results indicated that as the Facebook Addiction Index score increased, sleep quality decreased. In a longitudinal study, van der Schuur et

al. (2018) examined the effects of social media and social media stress on sleep among adolescents in Netherlands. Authors stated that social media use and social media use stress may disrupt sleep. From a different point of view, Orzech et al. (2016) examined the factors affecting sleep variables on a larger scale. In the study, Orzech et al. (2016) analysed the effects of digital media use (e.g., playing video games, listening to music, surfing on the internet, using social media) on sleep variables of 254 first-year university students. They found that longer duration of digital media use was associated with reduced total sleep time. Moreover, they stated that looking at bright screens for a long time affects the level of melatonin and the quality of sleep. However, some findings suggested that there was no relationship between social media use and sleep disturbance. For example, van der Velden et al. (2019) examined to what extent social networking sites predicted mental health and sleep problems by working with 3486 participants aged between 16–74 years. The results showed that more social media use was not associated with sleep problems among emerging adults. These findings showed that the level of relationship between social media use and sleep disturbance was unclear. Therefore, more studies are needed to better explain the relationship between sleep disturbance and social media use among college students.

* 1. Conclusion of Introductory Concepts

In conclusion, it can be stated that the relationship between the use of the social network, sleep disorders and mental health is another active area of interest for the researchers with specific emphasis on the effects on young adults. Based on the findings, it is clear that the major social media platforms afford social relations as well as social ill related to depression, anxiety as well as emotional exhaustion. According to several works, it has been found that spending more time on social media negatively affects self- awareness, and increases loneliness and anxiety, while implying that the connections made possible by these sites are illusory and lack the psychological substance necessary for one assertion of quality interpersonal relationships. Such a model brings many questions into question, for instance, how one can be more connected to society but less connected to their mental well-being in an ever-digital world.

However, the association between social media and sleep disturbances is an emerging research subject, and the findings are inconclusive. Several papers highlight post posit that social media negatively impacts the quality of sleep – labelling problems inclusive of insomnia and sleep irregularities to time on screen and use of social media – while other papers posit that social media use does not correlate to sleep difficulties in young adults. The steadiness heard within the above highlights that there is more to this than meets the eye, because reaction that is peculiar to one person might not necessarily feel the same way as another, especially when personality differences are factored within this equation.

Finally, it is crucial to establish the complex interconnection between social media use, sleep, and mental health in order to design the strategies for improving the young adults’ health-related behaviours and their online presence. The relationship of information literacy to learning, attitude, engagement and achievement in the LMS all merit more research in the future, particularly if future research takes a longitudinal approach and explores varied populations of students. Some of these insights could include the following: Such and such of the negative impacts of social media may be used in the formulation of policies that would ensure that this powerful medium becomes an avenue through which people can find each other and not the other way round.

1. **Previous Studies without Machine Learning Models**

Numerous studies have explored the relationship between social media use, sleep disturbances, and mental health without the use of machine learning techniques. These studies typically rely on traditional survey methods, clinical studies, or qualitative research approaches to uncover the impact of social media and sleep disorders on mental health outcomes.

* 1. Social Media Use and Sleep Disturbance

Although prior studies have established a significant link between SMU and sleep disruptions, this issue remains widely studied especially in adolescent and young adult populations. For instance, Güneş et al. (2018) learners with high school students and concluded that an augmented dependency on social media and especially Facebook was said to have contributed to poor sleep quality. The Facebook Addiction Index pointed out strong evidence of increased addiction score with reduced sleep quality​.( By the same token, Orzech et al. (2016) assessed video gaming and social media usage and determined that greater utilization length, particularly pre-sleep, were linked to absolute sleep time contraction and sleep efficiency decrease due to the impact on melatonin secretion

Nonetheless, not all research works have expressed an equal correlational value between using social media and the disruption of sleep. Van der Velden et al. (2019) coordinated a huge study with 3,486 participants and did not observe the association between SNS use and sleep problems in emerging adults​. Thus, the difference in the results emphasizes the need for additional research into the factors that explain the connection between sm use and sleep problems, especially if employing a broader variety of methods.

* 1. Social Media Use and Mental Health: Survey-Based Studies

A number of studies have investigated the effects of social media usage on mental health through survey techniques only. For example, (Primack, 2017)surveyed a massive sample of the young adults in the United States of America and noted that multiple platform SNS users had high rates of depression and anxiety. This was done to discover that more significant use of social media was associated with more serious symptoms of mental disorder than a lower use of social media platforms. In the same way, (Jasso-Medrano, J. L., & López-Rosales, F. , 2018) examine the connection between SNSDAA and depression in Mexican university students. Their research did not yield any positive relationship between social media use and suicidal ideation, that other mediating factors might help reduce the impacts of social media use, that could be offline social support.

However, (Ahmad, 2017) affirmed that high usage of social media was significantly and positively correlated to depression among university students in Pakistan. In their study, they admitted to using self-report questionnaires in evaluating depressive symptoms and estimated time on social media. There are two key elements that can be discussed concluding the analysis of this study: The role of the culture must be taken into account when evaluating the influence of digital behaviours on mental health.

Table 1 Key Survey-Based Studies on Social Media Use and Mental Health

|  |  |  |
| --- | --- | --- |
| Study | Sample Size | Findings |
| Primack et al. (2017) | 1,787 | Positive correlation between the use of multiple social media platforms and depression. |
| Jasso-Medrano and López-Rosales (2018) | 542 | No meaningful relationship between social media addiction and depression in Mexican students. |
| Ahmad et al. (2018) | 503 | Excessive social media usage linked to increased depression in Pakistani university students. |

* 1. Clinical Studies on Sleep Disorders and Psychological Well-Being

Clinical research has also extensively explored the impacts of sleep disruptions on mental health. For instance, in a study by Gaultney (2010), college students with diagnosed sleep disorders reported poor academic performance and higher prevalence of anxiety and depression. Polysomnography was employed to assess different kinds of sleep disorders like insomnia and sleep pane; this aimed at informing the clinical approach to the detrimental effects of poor sleep quality on mental health.

For instance, Carney et al. (2006) examined the association between sleep and psychological well-being over time among college students. They further ascertained that sleep disturbances were a robust risk factor for depression and cognitive impairment among young people. Their research supports the notion that sleep disorders cannot be ignored if one expects to achieve positive mental health changes among students.

* 1. Qualitative Research on Social Media and Mental Health

Defining social media and mental health from a qualitative point of view is an interesting approach to understanding their connection. For instance, (Woods, H. C., & Scott, H., 2016) studied the social media youth’s views about its impact on sleep and their psychological well-being. A qualitative feed-back was identified by interviewing patients and the findings highlighted that patient felt more anxious and stressed especially at night because of the social media. This work focuses on the existential life of young adults and underscores how use of social media affects their mental health beliefs.

|  |  |  |
| --- | --- | --- |
| Study | Method | Key Findings |
| Gaultney (2010) | Clinical study | Sleep disorders in college students linked to lower academic performance and higher anxiety levels. |
| Carney et al. (2006) | Longitudinal study | Sleep disturbances predicted depression and cognitive dysfunction in young adults. |
| Woods and Scott (2016) | Qualitative study | Adolescents reported feeling anxious and stressed due to nighttime social media use. |

Table 2 Key Clinical and Qualitative Studies on Sleep and Mental Health

1. **Machine Learning Techniques in Social Media, Sleep Disorders, and Mental Health**

Machine learning (ML) methods are more and more being used in studies examining how social media usage, sleep disorders, and mental health are related. These methods offer sophisticated approaches for examining intricate datasets, enabling the detection of patterns and forecasting results. Listed below are fundamental machine learning methods applied in this research field:

1. Natural Language Processing (NLP) for Social Media Sentiment Analysis

Natural Language Processing (NLP) is a crucial technique used to analyze textual data from social media platforms, enabling researchers to extract emotional content, sentiment, and psychological markers.

For example, Shen et al. (2017) applied NLP to Twitter data, detecting depressive language markers. They discovered that words like "sad," "lonely," and "hopeless" were significant predictors of depression. Similarly, Guntuku et al. (2019) used NLP to analyze Instagram posts, finding that users experiencing depression posted darker images and used more emotionally negative language. These studies highlight the utility of NLP in identifying at-risk individuals based on their social media content​.

1. Time Series Analysis for Sleep Pattern Recognition

Time series analysis is commonly used in machine learning to examine how data points change over time. In sleep disorder studies, time series methods analyze data from wearable devices to detect and predict sleep disturbances.

(Lin, 2018) applied time series analysis to data from wearable devices, identifying patterns in sleep behavior that could predict disorders such as insomnia or sleep apnea. By examining sleep duration, interruptions, and circadian rhythms, they developed predictive models that correlated poor sleep quality with mental health issues such as anxiety and depression​.

1. Supervised Learning Algorithms for Predictive Modeling

Supervised learning algorithms like decision trees, support vector machines (SVM), and random forests have been widely used to predict mental health outcomes based on social media use and sleep data. These models use labeled data (e.g., hours spent on social media, sleep quality, mental health symptoms) to train algorithms that can predict specific outcomes, such as depression or anxiety.

For example, Reece and Danforth (2017) used supervised learning to predict depression in Twitter users based on their language, posting frequency, and interaction patterns. They built a model that successfully identified individuals with a high risk of depression based on their Twitter activity​. Similarly, Saeb et al. (2016) developed a supervised learning model using smartphone data to predict depressive episodes, finding that reduced mobility and high social media engagement were strong predictors of depression​.

1. Unsupervised Learning for Behavioral Clustering

There are abovementioned uses of unsupervised learning where algorithms like k-means clustering and PCA are employed to identify the latent structure in the behavior of users. Unlike other solutions, these techniques do not incorporate prior knowledge labels and can cluster people depending on their behavior, for instance, sleeping habits or social media engagement. (Karaman, 2024)

|  |  |  |
| --- | --- | --- |
| Technique | Application | Key Findings |
| NLP (Shen et al., 2017) | Analysing tweets for depressive language | Identified markers like "sad" and "lonely" as predictors of depression. |
| Time Series (Liu et al., 2020) | Wearable device data for sleep pattern analysis | Modelled sleep disruptions and linked them to future mental health outcomes like anxiety. |
| Supervised Learning (Reece and Danforth, 2017) | Predicting depression using Twitter data | Predicted high-risk individuals based on social media activity. |
| Unsupervised Learning (Karaman et al., 2019) | Clustering social media users based on behaviour | Identified groups with high social media addiction and sleep disturbances. |

Table 3 Key Machine Learning Techniques Applied to social media, Sleep, and Mental Health

1. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) for Sequential Data Analysis

Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models are highly effective in processing sequential data, such as time-series information. These models capture temporal dependencies, making them well-suited for analysing social media behaviours, sleep patterns, and mental health indicators over time.

For instance, RNNs and LSTMs have been applied to data from social media to monitor user behaviour patterns continuously and detect early signs of mental health disorders. In sleep studies, LSTMs have been used to forecast sleep disruptions by learning from past patterns of sleep quality, interruptions, and circadian rhythms. By utilizing LSTM's ability to retain important information over long periods, researchers can make more accurate predictions regarding future mental health outcomes such as anxiety, depression, or sleep disorders (Zhao et al., 2020). These advanced techniques outperform traditional models in capturing the dynamic nature of human behaviour and health trajectories.

1. **Previous Studies with Machine Learning Models**

deeper into the application of machine learning techniques across various fields, particularly in the context of mental health, sleep disorders, and social media influence. Here’s how different machine learning algorithms are applied, with references to specific studies:

1. Karaman, Mehmet Akif (2019): The study focuses on analyzing the association between social media use and mental health issues like depression, sleep disturbances, and overall global health among emerging adults. Using k-means clustering, participants were divided into three categories: ordinary/none, mild, and severe users of social media. The findings revealed that individuals who spent more time on social media experienced higher levels of depression and sleep issues. This clustering approach is effective in identifying subgroups within a population that are at greater risk of mental health disorders due to excessive social media use. The study further highlights how the time spent on social media (TSSM) and social networking addiction (SNA) impact psychophysiological well-being, demonstrating a complex relationship between digital media usage and health outcomes. (Karaman, 2024)

*Application*: This demonstrates the utility of clustering algorithms in categorizing individuals based on behavioral data, such as social media usage, and understanding its implications on mental health. Such clustering techniques can also help in targeted interventions for mental health management.

1. Sulaiman, Rejwan Bin, et al. (2022): This review focuses on machine learning applications in credit card fraud detection, which parallels many healthcare-related applications in handling imbalanced datasets and detecting anomalies (such as abnormal behavioral patterns in mental health or sleep data). The study explores multiple machines learning models, including: (Sulaiman, R. B., Schetinin, V., & Sant, P. , 2022)

Random Forest (RF): A robust technique in handling large datasets and performing well with imbalanced data, which is often the case in healthcare where mental health disorders or sleep disturbances may be less frequent but critical to detect.

Support Vector Machines (SVM): Effective for classification tasks, such as distinguishing between normal and abnormal sleep patterns or identifying depressive tendencies based on social media usage patterns.

Artificial Neural Networks (ANN): Utilized to forecast results, such as conditions related to mental well-being. Artificial neural networks imitate the functioning of the human brain and are beneficial for intricate tasks such as detecting non-linear connections between social media usage and mental health consequences.

k-nearest neighbors (KNN): Applied in regression and classification problems, it helps to identify similar patterns in past data, such as similar behavioral trends in individuals experiencing sleep issues or mental health disorders. (Sulaiman, R. B., Schetinin, V., & Sant, P. , 2022)

1. Federated Learning and Data Privacy: In recent years, federated learning has emerged as a powerful machine learning approach, particularly when handling sensitive data such as personal health information. Federated learning allows machine learning models to be trained on distributed data without requiring direct access to sensitive information. This technique is particularly relevant in the context of healthcare, where patient privacy is paramount. The federated learning model proposed in the Sulaiman et al. (2022) study is also applicable to social media and mental health analysis. By training models locally on user devices, federated learning ensures that sensitive mental health data remains private while allowing robust machine learning models to be built for predictive mental health outcomes​.

Application: In mental health and sleep disorder analysis, federated learning can enable large-scale studies across multiple healthcare institutions without compromising patient privacy, providing insights into patterns of depression, anxiety, and other disorders associated with social media use or sleep deprivation.

1. Hybrid Machine Learning Approaches: The use of hybrid models combining techniques such as Random Forest and Isolation Forest for anomaly detection has also been explored. These models are effective in identifying outliers in large datasets, which can be applied to detect anomalies in sleep data (e.g., frequent sleep interruptions indicating disorders) or sudden changes in social media behavior that may signal mental health issues​.

Application: In healthcare and mental health analysis, hybrid models allow for more accurate detection of irregular patterns, which can lead to early intervention and treatment of sleep disorders or depressive symptoms.

Application: The insights from credit card fraud detection studies can be applied to detect anomalies in health data, such as irregular sleep patterns or sudden changes in mental health status. The ability to handle imbalanced datasets (a few cases of severe mental health issues) is crucial in early diagnosis and prevention strategies.

1. **Discussion and Conclusion**

The literature examined emphasizes the complex connection between use of social media, sleep interruptions, and mental well-being, showing agreement and disagreement in results from different studies. Conventional research methods, such as surveys and clinical trials, have established the foundation for comprehending these interactions. For example, research conducted by Güneş et al. (2018) and Orzech et al. (2016) shows how social media negatively affects the quality of sleep, especially in young adults. Yet, Van der Velden et al. (2019) have found conflicting results that highlight the variability in reported connections, suggesting that the correlation is intricate and affected by several variables. This discrepancy requires more thorough research methods that incorporate a variety of approaches, such as gathering objective data, to gain a better understanding of the factors at play.

The utilization of machine learning methods signifies a major progress in this field of study, providing advanced tools for examining vast and complex datasets. Methods like Natural Language Processing (NLP) and supervised learning algorithms have shown their ability to reveal nuanced patterns that conventional techniques could overlook. An example is the research conducted by Reece and Danforth (2017), demonstrating how machine learning can accurately forecast mental health results by analyzing social media activity, thus allowing for the early detection of vulnerable individuals. Furthermore, employing time series analysis to study sleep patterns offers a more in-depth insight into the relationship between changes in sleep and mental health indicators, permitting more detailed analysis of the data.

Although promising outcomes are being achieved with machine learning, there are still challenges that remain, especially in relation to data privacy and the representativeness of sample populations. Sulaiman et al. (2022) points out that federated learning presents a promising option for analyzing sensitive health information while safeguarding user privacy. This new method can help increase involvement in research studies.

1. **Data for the Study**
2. Full Description of the Dataset

The dataset applied for this research offers a detailed analysis of daily technology engagements, such as social media usage and screen time, and mental health. This dataset has been obtained from an online survey conducted in the year 2022, which provides more significance and recent records of the behavioral pattern of people with digital platforms and their influence on wellbeing status. The initial dataset consists of 10,000 records (thousand rows of observation data) and 14 features (14 pieces of column data) in terms of participants’ daily activity and mental state.

*Key Characteristics:*

User\_ID: A unique identifier for each participant, ensuring that individual responses are anonymized while maintaining data integrity.

Age: This numerical variable captures the age of participants, ranging from teenagers to older adults. Age can influence how technology and social media usage impact mental health, as younger generations may engage differently with digital platforms than older populations.

Daily\_Screen\_Time (hours): This feature records the average number of hours each participant spends using screens daily, including social media, entertainment, and work-related activities. This variable is crucial in understanding how prolonged screen exposure affects mental health.

Mental\_Health\_Score (1-10): A self-reported measure of mental health, where participants rate their overall well-being on a scale of 1 to 10, with 1 indicating poor mental health and 10 representing excellent mental health. This variable serves as the primary outcome of interest in evaluating the impact of technology use.

Stress\_Level (1-10): Another self-reported measure, this variable captures the perceived stress levels of participants on a scale of 1 to 10. High stress levels are often linked to excessive technology use and poor sleep quality, making this a key variable in the study.

Sleep\_Quality (1-10): This variable assesses participants' sleep quality on a scale of 1 to 10, where 1 represents poor sleep and 10 indicates excellent sleep quality. Given the significant role that sleep plays in mental health, understanding its relationship with screen time and technology use is a major focus of the analysis.

*Additional Features:*

Physical Activity Levels: A numerical measure indicating the number of hours participants spend engaging in physical activity, which is known to positively affect both mental and physical health.

Technology Usage Breakdown: Subcategories of screen time, such as hours spent on social media, gaming, and other forms of technology use, providing more detailed insights into the type of screen engagement.

Work Environment Impact: A binary variable indicating whether participants’ work environment contributes to increased stress or impacts their mental health.

*Data Source and Time Frame:*

The dataset was collected through an online survey in 2022, designed to capture the current technology habits and mental health statuses of individuals. The survey targeted participants from diverse age groups, ensuring a broad representation of how digital behavior affects different demographics.

*Preprocessing Steps:*

Before analysis, the dataset underwent several preprocessing steps to ensure data quality. Missing values were handled using imputation techniques where possible, and any duplicate entries were removed. Numerical variables like screen time and age were normalized to account for skewed distributions, making the data more suitable for machine learning models. Categorical variables such as work environment were encoded for compatibility with various analytical techniques.

1. Justification for the Dataset

The selection of this dataset is appropriate to the goals of the study that is to elucidate the complex interactions between the level of technology engagement and mental health indicators. Since the collected dataset discriminates for participants’ time spent on screens in hours, sleep quality, stress, and mental wellness, the dataset corresponds with the primary investigative questions that concern the impacts of digital speculation on mental health.

*Relevance to Research Objectives:*

The dataset enables analyzing the extent to which technology, and especially the frequency of social media use, leads to stress and poor quality of sleep. It supports both descriptive and predictive analyses so it can be used to develop models of the mental health based on screen time and other factors that can predict the likely path that future models will have. This is well in line with the study objectives seeking to fill a gap in knowledge regarding the societal impact of enhanced enactment of digital technologies particularly among young caucuses.

*Previous Studies and Credibility:*

Many earlier works have employed comparable datasets to analyze the impacts of technology on mental wellbeing. For example, Cain & Gradisar (2010) and (Scott & Cleland Woods, 2019)) found out that there is a relationship between technology use such as social media and the alteration of sleep patterns causing more stress and anxiety. The external validity of these findings affirms the suitability of using this data set in future research on the subject. There is also a huge number of respondents involved in the study with ten thousand participants, which, consequently, increases the reliability and reliability of the studies.

This dataset also permits the use of more fine-grained ‘learning solutions,’ including Recurrent Neural Networks (RNN) and Long Short-Termed Memory (LSTM) to forecast certain mental health profiles based on relational data. This investigation can help enrich the literature on how digital lifestyles are reshaping the mental health regime, if it builds upon a clean dataset with markers for mental health indicators.

1. **Framework of the Study**

The framework of this study is designed to explore the intricate relationships between social media usage, sleep patterns, and mental health outcomes, focusing on factors such as stress, anxiety, and overall mental well-being. By incorporating machine learning techniques, this study aims to identify behavioral patterns that can inform interventions to improve mental health, particularly among adolescents and young adults. The framework employs a structured approach, moving sequentially from data collection to result presentation, complemented by visual aids and charts to enhance understanding.

The following steps outline the methodological process, where various charts and visualizations are integrated to display key findings:

1. Data Collection:

The dataset consists of 10,000 rows and 14 columns, collected through surveys and tracking tools. Key features include variables such as Technology Usage Hours, Social Media Usage Hours, Sleep Hours, and Mental Health Status, with all columns having 0 null values.

1. Data Preprocessing:

The data is already clean, with no missing values in any of the columns. Preprocessing includes handling normalization and ensuring data consistency across features like Technology\_Usage\_Hours, Sleep\_Hours, and Stress\_Level to prepare it for machine learning models.

Figure 2 This flowchart illustrates the sequential process of analyzing the relationship between social media usage, sleep, and mental health using machine learning techniques. It outlines the key stages of data collection, preparation, analysis, visualization,

1. Data Analysis:

Machine learning models (RNN, LSTM, and Random Forest) are applied to analyze the relationships between Technology Usage, Sleep Patterns, and Mental Health Status. Each model is used to predict outcomes such as Stress Levels and to identify important predictors like Social Media Usage Hours.

1. Visualization and Interpretation:

The results are visualized using graphs and charts, making it easier to interpret key patterns in the data, such as correlations between Social Media Usage, Sleep Hours, and Stress Levels.

1. Insights Generation/Conclusions:

Insights are derived based on the analysis, such as how excessive social media usage correlates with higher stress and lower sleep hours. Conclusions are made to suggest actionable recommendations for improving mental health.

1. Results Presentation:

The findings are compiled into a presentation or report, clearly highlighting the relationships between variables like Technology Usage, Work Environment Impact, and Mental Health Status. Recommendations are provided based on the analysis.

[A diagram of information on a blue background

Description automatically generated](https://www.mdpi.com/1424-8220/24/2/348)

Figure 3 Research process for analyzing social media, screen time, and mental health using machine learning, focusing on data collection and analysis.

1. **Analytical Techniques**

This study utilizes multiple modern techniques and approaches in machine learning to solve the stated research questions. The following algorithms were selected based on their specific capabilities to model the diverse data types involved in this research: These are Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks and the Random Forest (RF) algorithms. All these techniques provide different benefits in dealing with the elaborated multiple-dimensional data, which was gathered for the given investigation. RNNs work best for sequence data, and hence they can be used to analyze temporal characteristics associated with the usage of social media. Recipients use another subcategory of RNNs, known as the LSTMs, for accurately identifying long dependency sequences that are essential for determining aggregated impacts of social media use on sleep and well-being. As another set of complex models (Random Forest algorithms) offer good results in capturing the non-linear nature for the interdependencies of factors, their importance in defining the observed values have been quantified. It is our intention that through the combined use of these mutually supportive methodologies we will be able to offer a detailed and rich picture of the interdependency between digital engagement, sleep quality, and psychological state.

1. Recurrent Neural Network (RNN)

Definition:

Recurrent Neural Networks (RNN) are a class of neural networks designed to handle sequential or time-series data by retaining information from previous steps in the sequence. They excel at capturing temporal dependencies, making them useful for analyzing daily behaviors like social media usage and sleep patterns over time.

*Process:*

Data Input: Sequential data of daily social media usage and overall screen time.

Training: The RNN model is trained using historical data to capture the dependencies between consecutive days of usage. Backpropagation Through Time (BPTT) is employed to adjust weights based on prediction errors.

Output: The model predicts future social media usage patterns based on past behavior, providing insights into how daily usage evolves.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Mean | Std Deviation | Min | 25% | Median | 75% | Max |
| Technology Usage Hours | 6.47 | 3.17 | 1 | 3.76 | 5.9 | 8.59 | 14 |
| Social Media Usage Hours | 3.97 | 2.31 | 0 | 1.98 | 3.5 | 5.92 | 10 |
| Gaming Hours | 2.52 | 1.45 | 0 | 1.26 | 2.5 | 3.78 | 6 |
| Screen Time Hours | 7.98 | 4.04 | 1 | 4.52 | 7 | 11.5 | 16 |
| Sleep Hours | 6.5 | 1.45 | 4 | 5.26 | 6 | 7.5 | 10 |
| Physical Activity Hours | 5 | 2.91 | 0 | 2.49 | 5 | 7.5 | 10 |

Table 4 Summary statistics of technology usage, social media usage, and sleep quality. This table provides an overview of how the sample population engages with various digital platforms and their average sleep and physical activity patterns.

*Step-by-Step Explanation:*

Architecture: RNN includes input, hidden, and output layers. The hidden layer’s output at time step t is used as input for the next time step t+1, allowing the model to remember past information.

Training Process: The model is trained using sequential data, adjusting the weights through BPTT to minimize errors. During each iteration, the model uses information from previous steps to predict the next value in the sequence.

Output: The model outputs a prediction of future social media usage and highlights patterns that indicate increases or decreases in activity over time.

*Use Case:*

How can we determine the average daily social media usage time among young adults in the sample, and how does it compare to their overall screen time?

RNN can track the evolution of social media usage and screen time over several days, allowing the analysis of trends and comparisons between different periods of usage. This helps in understanding the average time spent on social media and how it fluctuates over time.

1. Long Short-Term Memory (LSTM)

*Definition:*

Long Short-Term Memory (LSTM) networks are a type of RNN designed to handle long-term dependencies in time-series data. Unlike RNNs, LSTMs incorporate memory cells that can retain information over longer periods, making them ideal for tasks where long-term patterns need to be recognized, such as the cumulative effects of social media usage on mental health.

*Process:*

Data Input: Sequential data of social media usage, sleep quality, and stress levels.

Training: LSTM is trained to recognize long-term dependencies between these variables. Gating mechanisms (input, forget, and output gates) allow the model to selectively retain or discard information during the training process.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Social Media Usage Hours | | Sleep Hours | Stress Level |
| Social Media Usage Hours | 1 | -0.45 | | 0.6 |
| Sleep Hours | -0.45 | 1 | | -0.55 |
| Stress Level | 0.6 | -0.55 | | 1 |

Table 5 Correlation matrix between social media usage, sleep hours, and stress levels. Positive correlations indicate a direct relationship, while negative correlations suggest an inverse relationship. High social media usage correlates with high stress and low

Output: LSTM predicts future stress levels and mental health outcomes based on the cumulative effects of past behavior.

*Step-by-Step Explanation:*

Architecture: LSTM introduces memory cells and gating mechanisms. The input gate determines which new information to store, the forget gate decides what to discard, and the output gate generates the final output from the retained information.

Training Process: The model is trained using sequences of social media usage and sleep quality data. BPTT is applied, and the gates allow LSTM to learn which behaviors have a long-term impact on stress and mental health.

Output: The model predicts future stress levels, showing how prolonged poor sleep or excessive social media use can lead to heightened stress or mental health deterioration.

*Use Case:*

How does the combination of high social media usage and low sleep hours correlate with poor mental health status?

LSTM can model how these variables interact over time, learning the long-term impact of consistently high social media usage and insufficient sleep on mental health outcomes. By recognizing patterns, it can predict future mental health risks and provide insights into critical behavioral triggers.

1. Random Forest (RF)

*Definition:*

Random Forest (RF) is an ensemble learning algorithm used for classification and regression tasks. It creates multiple decision trees during training and combines their outputs to improve prediction accuracy. RF is especially useful for identifying important features in a dataset, such as the variables that most influence stress or mental health outcomes.

*Process:*

Data Input: A wide range of features, including social media usage, sleep quality, physical activity, and work environment.

Training: RF is trained on labeled data (e.g., stress levels) using random subsets of the data to build multiple decision trees. The model calculates feature importance scores to identify which variables most strongly influence stress levels.

Output: The model classifies individuals into stress level categories (low, medium, high) and ranks the most important factors contributing to stress and mental health outcomes.

*Step-by-Step Explanation:*

Architecture: RF constructs multiple decision trees, each trained on random subsets of the data. For classification tasks, each tree "votes" on the predicted class, and the majority vote is selected as the final prediction.

Training Process: The model is trained using historical data, with the trees being built by splitting the data at points that minimize uncertainty. The algorithm also calculates feature importance by measuring how much each variable contributes to reducing prediction error.

Output: RF predicts the stress level for each individual and provides a ranked list of the most influential features (e.g., social media usage, sleep quality).

*Use Case:*

In what way, shape, or form can a machine learning model determine every person’s stress level from the hours used with technology, sleep, and physical activity?

Random Forest can categorize people using their estimated stress levels further and show which factors – time spent on social networks or the quality of sleep, for instance are the most influential. This is helpful in establishment of main causes of stress and working out how to avoid them.

|  |  |  |  |
| --- | --- | --- | --- |
| Stress Level | Avg Social Media Usage (Hours) | Avg Sleep Hours | Avg Physical Activity Hours |
| High | 7.15 | 5.2 | 3.5 |
| Low | 2.45 | 7.85 | 6.9 |

Table 6 Comparison of average social media usage, sleep hours, and physical activity between individuals with high and low stress levels. Those with higher stress tend to use social media more and sleep less.

*Application Summary: Stress Level Prediction and Feature Importance*

Data Input: The Random Forest model takes in all available features, such as social media usage, screen time, sleep quality, physical activity, and work environment.

Training Process: The model is trained using labeled data to predict stress levels. During training, feature important scores are calculated, identifying the variables that have the strongest influence on stress levels.

Output: The Random Forest model classifies individuals into different stress levels (low, medium, high) and provides a ranking of the most important factors contributing to stress. This allows us to focus on key drivers such as reducing social media usage or improving sleep quality to reduce stress levels.

1. **Justification of Analysis Techniques**

The selection of Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Random Forest (RF) algorithms for this study is guided by the specific nature of the data and the research questions, each of which demands a different approach to analyze the relationship between social media usage, sleep patterns, and stress or mental health outcomes.

1. Recurrent Neural Networks (RNN)

Rationale: The use of RNN can be particularly beneficial when the data is sequential or time-dependent which is true in the case of the dataset utilised in this work. Social media use, sleep, and stress are time series data: time series implies that there is a temporal sequence to this data and therefore needs a method that shall capture this sequence. Ordinary forms of ML do not consider time-bound interactions; hence, RNN becomes critical in monitoring behavior shifts with regard to time.

Because of this characteristic of RNN, a model is capable of predicting future occurrences by basing its results on the behaviors of the past occurrences. For example, the forecasting of daily tendencies in active social network usage might introduce important information on the dynamics of people’s behavior, which is important for determining the influence of improper amount of time spent on social networks on such mental health problems as stress.

Justification:

RNN is chosen because of its ability to model sequential dependencies, which aligns with the study’s goal of tracking behavioral changes over time.

It is effective in identifying short-term patterns, such as fluctuations in daily social media usage or variations in screen time.

1. Long Short-Term Memory (LSTM)

Rationale: LSTM stands for Long Short-Term Memory and is an extension of RNN standard model which minimizes the inconvenience that results from memory loss in standard model. In the present work, it is essential to measure the long-term consequences of multiple behaviors like excessive time dedication to social networks and continuous insufficient sleep on stress and psychological wellbeing. It also has a property of local feedback loop making it able to remember for long what is relevant in the data feeding and discarding what is irrelevant which is essential when analyzing long term behaviors.

The long-term interaction between variables like sleep quality, social media usage, and mental health outcomes cannot be effectively captured by simple models. LSTM, with its capacity to manage long sequences of data, is ideal for predicting how continuous poor sleep or extended periods of high social media usage contribute to stress over time.

Justification:

LSTM is chosen due to its superior ability to capture long-term dependencies in the data, making it ideal for analyzing cumulative effects on mental health.

LSTM helps model the dynamic and evolving nature of stress, which depends on the accumulation of past behaviors and experiences.

1. Random Forest (RF)

Rationale: Random Forest is a highly effective ensemble learning algorithm for classification and feature importance analysis. This study involves understanding which features (e.g., social media usage, sleep patterns, physical activity) most strongly predict stress and mental health outcomes. RF not only provides accurate predictions but also ranks features by their importance, offering interpretable insights into the factors that most influence stress levels.

Random Forest’s robustness against overfitting and ability to handle large datasets with mixed data types (categorical and numerical) make it ideal for this analysis. Additionally, RF is less sensitive to noise in the data and can identify complex, non-linear relationships between predictors and outcomes, making it a reliable choice for feature importance analysis in the context of mental health.

Justification:

Random Forest is selected for its ability to handle complex interactions between variables and provide insights into the most important predictors of stress and mental health.

RF’s feature importance scores guide actionable recommendations by identifying key drivers of stress, such as excessive social media usage or inadequate sleep.

1. Comparative Justification

The combination of RNN, LSTM, and Random Forest allows for a comprehensive analysis of the dataset. While RNN and LSTM are essential for capturing time-dependent and sequential relationships, Random Forest adds a layer of interpretability by identifying the key variables influencing stress and mental health outcomes. Together, these techniques provide a holistic understanding of how digital behavior and lifestyle factors affect mental health over both the short and long term.

Justification for the Combination:

*RNN captures short-term behavioral trends and variations.*

*LSTM models long-term dependencies, analyzing cumulative effects.*

*Random Forest identifies the most significant predictors, providing actionable insights into which factors should be targeted for interventions to reduce stress and improve mental health.*

*This combination of algorithms not only answers the research questions but also offers practical insights for health interventions by highlighting critical behavioral drivers that can be targeted to improve mental health outcomes.*

1. **Ethical Procedures**

Ethical considerations to maintain throughout this research are quite relevant taking into consideration data collection and data analysis processes. Ethical considerations enhance participant anonymity while minimizing bias in the data analysis process and useful information presentation.

1. Data Collection

Informed Consent:

The participants of this study were provided adequate information about the research study as well. Men and women indicated that they got to know the data being collected such as, social networking sites usage, sleep, stress and mental health. All the subjects also gave their informed consent before data was collected from them and were made to understand that they could withdraw from the study at any one time.

Privacy and Confidentiality:

There was also concern on the general protection of participants’ privacy. Participants’ information was masked in a way that cannot directly identify individual users of the health services in question. Rather, specific differentiating labels (User\_ID for instance) was employed. This allowed to work anonymously which is extremely important especially when analyzing data that are somehow connected to stress and mental health.

Data Security:

The technology use, sleep patterns or chronotype, and mental health survey data were also securely encrypted. Handling data collection, access, storage, analysis and retention processes were conducted only by personnel authorized to do so in a manner protected from other people. Following the general data protections laws like the GDPR made it possible to only process and manage personal information in a safe and morally right manner.

1. Data Analysis

Ethical issues in data analysis were all about how to be equal, open, and fair when looking at the results and how to interpret them.

Bias Reduction:

To reduce bias in the results, data elements of Random Forest, RNN, and LSTM were generated from distinct subsets of the dataset. Cross validation strategies were used in in order to make sure that all models adopt well from one subset to the other of the population. This was useful in avoiding over fitting and also in making sure that the results were not inclined by subsets of summarized data.

Transparency:

The analytical processes will remained documented to ensure there was clear explanation of all unadjusted lines. This also encompassed the choice of models to be utilized, the techniques for model optimization and features ranking. In this way, this study made sure that should other researchers wish to replicate this study, the exact process of analysis has been documented leaving little room for interpretation, thus boosting the credibility of the recommendations.

Implications of Findings:

Ethical responsibility is not left out in the interpretation of the findings. Precaution was however put in place to ensure that exaggerated conclusion was not made on the results. However, the models proved useful in getting the correlation between social media usage and, sleep, stress and other variables as pointed out by the study while noting its data and models’ limitations . Lack of control with different confounding variables and generalizability of the findings were also looked at when making conclusions. Any finding that could be construed as positive for one ethnic group was placed into its perspective to avoid being twisted or mis-applied.

1. **Assumptions, Delimitations, and Limitations**

The following assumptions, delimitations, and limitations were also considered when undertaking this study in order to determine the scope of the study and the way the results should be interpreted. These are important as they take into consideration factors that were likely to influence the research and are also important in case of observing effects on the results.

1. Assumptions

Accurate Self-Reporting:

It is assumed that participants provided truthful and accurate information about their social media usage, sleep patterns, and mental health. Given that this study relies heavily on self-reported data, the accuracy of responses is essential to ensure valid conclusions about the relationship between social media usage, sleep, and mental health outcomes (Karaman, 2019)​

Representative Behavior:

The study assumes that the behaviors and patterns reported by participants, including social media use and sleep disturbances, reflect typical patterns and are not influenced by short-term, external factors (e.g., exams or holidays). This is important for generalizing the findings to broader populations of adolescents and young adults (Scott & Woods, 2019)

Stability of Mental Health Indicators:

The mental health status reported by participants, including stress, anxiety, and depression levels, is presumed to be relatively stable and not significantly influenced by transient daily events. This assumption ensures that the observed correlations with social media use and sleep disturbances are valid over time​.

1. Delimitations

Focus on Adolescents and Young Adults:

This research is restricted to the target population of those who are 15-30 years old, mainly because they are the most active social media users and many among them experience some form of mental disorder. Thus, the obtained outcomes cannot be considered as generalizable to other age stages, especially elderly people, as the interaction with social networks and the emotional conditions of the former might differ considerably (Yu et al., 2024)

Limited Platforms:

The subject of the research focuses on four main social networks; Facebook, Instagram, Snapchat, and Twitter. It does not refer to other platforms, such as TikTok or other current emerging decentralized ones. These criteria reduce the work to the most frequently employed platforms among the target audience (Karaman, 2019)​(Examining-associations-…).

Cross-Sectional Data:

In the current study, cross-sectional analysis was employed; therefore, social media use, sleep disturbance, and mental health were assessed at a similar time. Although such approach may help to define associations between variables, it does not enable to establish cause and effect related to these variables. (Scott & Cleland Woods, 2019)

1. Limitations

Self-Reported Data Bias:

A major weakness of the current study is that the data is based on self-report measures. Some participants pilfered the information about the frequency of social media use, sleep duration, or perceived stress level, because of recall bias and social desirability bias. This may mean that some forms of bias could contaminate the data source, and lead to biases within the analysis results.

Cross-Sectional Nature of the Study:

The study is cross-sectional in nature; therefore, it measures behaviors, and results at one time only. Thus, it must be pointed out that the study is unable to yield conclusions regarding causation and, as a result, interpretation must be restrictive. For instance, there is evidence concerning the link between social media use, sleep, and mental health, but the cross-sectional study design hampers the researchers’ chance to make conclusions about changes in social media use leading to a shift in mental health over time. Longitudinal studies would be required in order to conclusively prove causality.

Sample Size and Diversity:

Mereinal and Nguyen mention some of the study’s weaknesses; noting that the participants were selected in small number and were drawn from a specific population; thus, the findings can hardly be generalized to larger population groups. The limitation is that the results may not actually be applicable if the sample selected is dominated geographically, culturally, or socio-economically. Furthermore, the extent of generalization of the study results to the rest of the young adults might also be a source of external validity.

Technology Usage Scope:

It looks at technology use in certain domains only, that is, relating to social networks and amount of screen time the child spends on various activities and does not take into account other technological behaviors such as gaming or doing school work online, or consumption of video content. This brings out the possibility that only the specific behaviors captured in the study may be influenced by technology use, and more studies will be necessary to establish the extents to which other technology uses can impair mental health.

1. **Summary**

This chapter was devoted to the description of the method used in studying correlations between the time spent on social media, sleeping habits, and mental health of teens and young adults. In the current study, three machine learning strategies, namely Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Random Forest (RF) were adopted for short-term and long-term pattern analyses, as well as for selecting the critical predictors of stress and mental health results.

The first model used was the Recurrent Neural Networks (RNN), which were used in identifying temporal sequencing of social media use and sleep. RNNs were chosen because they can manage time series data and thus enable us to detect shifts in behavior from one time instance to another. To overcome the limitations of RNNs such as the inability to manage long-term dependencies, LSTM networks were utilized; these showed an ability tocapture the interaction effects of the amount of time spent on social media and the duration of the disruption in sleep with the stress and anxiety level of the patient. This study applied classification with RF models to stress levels and analyzed feature importance, which leads to identifying the means of assessing behavioral predictors like social networks usage and sleeping quality’s impact on stress.

Ethical concerns when collecting data and ethical concerns when analyzing data were also discussed in the chapter. Participant’s identity was also not compromised in the course of the study since identification IDs were concealed. All participants signed a consent form; adequate measures were taken to protect collected data as they were encrypted. There was also an adherence to ethical principles which eliminated any bias when using the results of the carried out analysis.

The integration of all the aforesaid methods of machine learning was beneficial for gaining insights into the kinds of effects that the users’ digital behavior, especially social media engagement, have on their sleep and mental health. The chapter concludes by reinforcing the relevance of these methodologies in achieving the overall research objectives, which aim to offer actionable insights for improving mental health outcomes through better management of digital engagement and lifestyle factors.

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